SIMULATION PLATFORM FOR EARTHQUAKE PERFORMANCE EVALUATION OF URGENT MEDICAL CARE NETWORKS

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Abstract: *Emergency and Urgent Medical Care (EUMC) is a crucial activity to ensure survival and recovery of severely injured people after a major seismic event. It requires planning, coordination, and the ability to rapidly mobilize resources and personnel at different levels. An EUMC capable of responding to a severe seismic event must be the result of a well-thought design with a capacity to anticipate the consequences at various system levels. This paper describes the main concepts of a new model and implementation of an earthquake simulation platform for the EUMC network, SimPlaNeR, which integrates current research at the physical and operational aspects of the network in Chile. The model includes seven major technical modules, namely seismic hazard, building exposure and EUMC network characterization, network performance, patient flow, risk computation, and network planning, in addition to a middleware that generates the interactions between modules and gives access to a resource data lake. The platform engine deals with two macro-models, one describing the detailed physical performance of the built environment, in particular the EUMC assets, and the implications in terms of the provision of medical care, and another, which is an operational network and facility model, based on discrete event simulation and including the different phases of patient transportation, medical assistance, and patient outcome. Each patient carries a clock that monitors its health state at each instant of the simulation. Results of SimPlaNeR enable quantitative evaluation at the decision maker level of very technical aspects present at the different interventions levels of the model. Moreover, the planning module allows the evaluation of the deployment of alternative resources to improve the response such as field hospitals, first responders and better evacuation and transportation of the injured, better coordination of resources and personnel, and criticality of the EUMC assets. The paper concludes that the platform may have a substantial impact in the improvement of the response of EUMC networks in Chile.*

1. Introduction

As part of the Emergency and Urgent Medical Care (EMUC) system, the Primary Care Units (PCUs) and the Hospital Emergency Departments (HEDs) are the entrance door of the injured after a severe earthquake, and as such needs to be prepared to respond effectively during an emergency. However, since HEDs are usually strongly demanded in normal times, the situation becomes even more critical during disasters as a result of the: (i) impact in the triage and registration due to the significant surge of critical patient arrivals; (ii) lack of medical resources and space to accommodate the increase in demand; (iii) decrease in capacity of the facility due to functional damage caused by the event; (iv) increase on non-related disaster victims; (v) interoperability problems with other components of the hospital; (vi) lack of medical personnel at all levels; (vii) malfunction of other interdependent lifelines and utilities; (viii) internal communication problems; (ix) supply chain problems; and (x) a large variety of other aspects, such as the difficulty in the transportation of incoming and outcoming patients.

HEDs are complex systems (subunits) within a hospital and maintain strong interactions with other hospital systems, such as imageology, laboratory, blood bank, operating rooms, hospitalization beds, etc., and hence simulation plays a fundamental role in modelling such complexity, and supporting good decision-making at the operational, tactical, and strategic levels of the hospital (Gul y Guneri 2015).

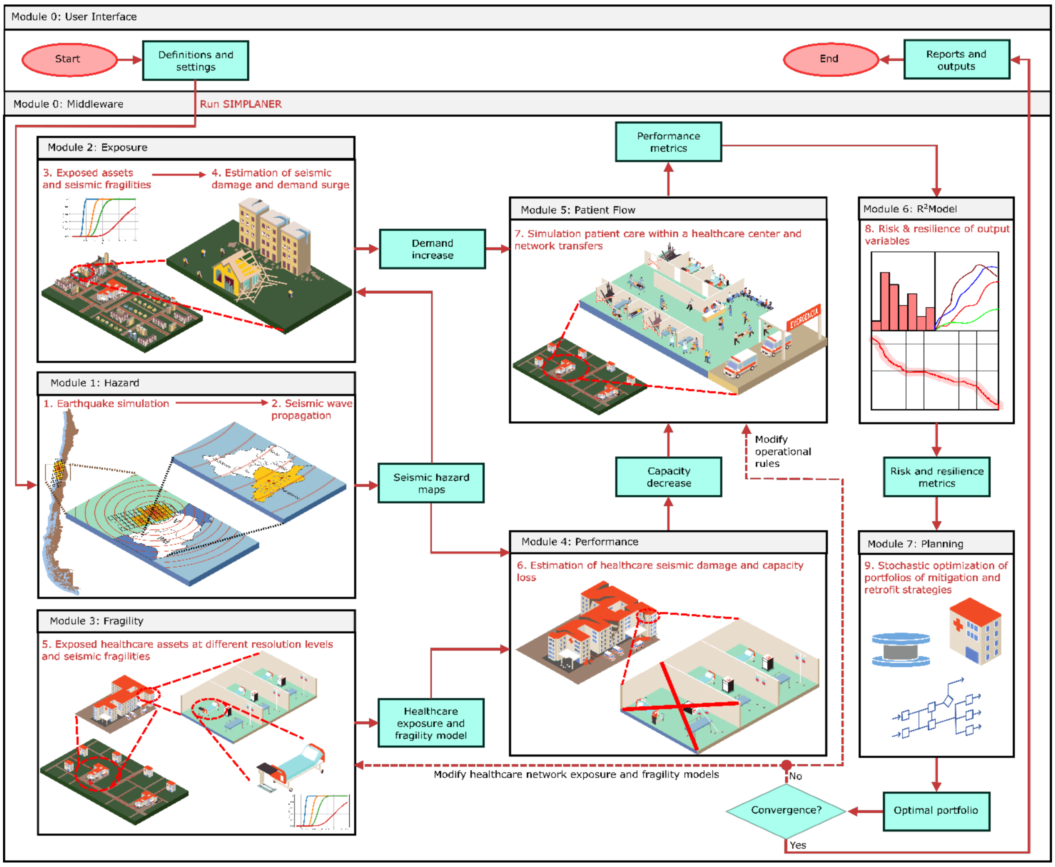


Figure 1 Scheme of the flow of information in SIMPLANER

The literature in modelling HEDs is large, and there are very complete accounts of such work (e.g., (Gul y Guneri 2015)). However, a small subset of these studies relates to modelling of the ED operations during disaster times. Indeed, most of the simulation analyses deal only with optimizing the workflow of patients due to the patient surge, the efficient use of ED resources, define optimal staff levels and allocation of medical resources, show how different arrival patterns and victim travel times affect the ability to treat patients, use generic simulation models capable of representing the operations of a wide range of hospitals given an earthquake disaster situation, and study different simulation and optimization methodologies, among others (e.g., (Günal y Pidd 2010)). In summary, studies have mostly focused on the treatment of patients rather than in the interlocking between earthquake consequences and patient welfare, which is our goal.

Thus, the major novelty of this work comes from: (i) connecting the seismic performance of PCUs and HEDs, including the structural, non-structural and equipment damage with the functional performance of the system after the event; (ii) scaling up the analysis to model the regional scale integrated performance of the complete network of PCUs and HEDs under an extreme event, considering the different complexities of HEDs and the possible transfer of resources and patients between healthcare units; (iii) incorporating a complete city risk model to quantify the expected surge of patients and the transportation times to the assigned PCUs and HEDs; and (iv) including a network planning model for the integrated physical-functional network of PCUs and HEDs, based on two-stage stochastic optimization.

To do this, we propose a new platform denoted SimPlaNeR (Simulation Planner for Network emergency Response). The platform has 7 modules, plus a middleware that does the coordination of the modules, and a user interface jointly designed with the system users, as presented in Figure 1. The modules are: (i) seismic hazard; (ii) city and network exposure; (iii) system fragilities; (iv) system performance; (v) patient flow; (vi) risk analysis; and (vii) network planning and optimization. This research also includes the study of two real-case situations, one in the Southeast Metropolitan Healthcare Service (SMHCS) of the city of Santiago, and the other, the Healthcare Service of the Maule (HCSM) region in Chile. This is still an ongoing research effort at the time of this article.

2. Conceptual Framework and Software Structure

2.1. Conceptual Framework

PUCs and HEDs constitute a complex network, which mathematical representation becomes more sophisticated as we include the interdependencies with other lifelines, such as the transportation model of critical patients, and the decrease in capacity experimented by the system as a result of physical damage in the structural, non-structural and medical components. As a starting point, the network is deployed on a geographical setting exposed to an earthquake hazard, which is characterized by the subduction and crustal seismicity dominant in Chile (Module 1, M1). The damage of the building inventory is based on a more general risk model of the built environment (e.g., OpenQuake (Pagani et al. 2014)) (Module 2, M2). This general model leads to a geographical distribution of the injured, which are transported into the PCUs and HEDs. A realistic transportation model for the city produces the time needed to transport patients. In the Chilean healthcare system, patients may also go through an intermediate layer of PCUs before reaching the HEDs depending on several factors; however, for the most critically injured, once they are stabilized in these PCUs, they are derived into the corresponding HEDs. As patients arrive to PCUs and HEDs, the medical attention process begins (Module 5, M5), and a Discrete Event Simulation (DES) model simulates that process. This model considers the drop in the capacity of the system (Modules M3 and M4), and based on that constraint and the medical priorities, assigns the medical resources. The surge in patient demand (M2), and the decrease of available resources (M3 and M4), eventually creates longer waiting times for the patients (M5), which medical condition is monitored in real (simulation) time. All the stochastic evaluations are performed under the conceptual framework of a typical risk analysis model (Module M6), and results are used for the planning tool based on stochastic optimization (Module M7), which algorithm separates the preparedness measures (previous to the event), with the mitigation measures (post event).

2.2. Software architecture

Other simulation platforms exist in practice (e.g. (Pegden 2023; FlexSim 2023)) which could probably be used in modeling some of the components considered in this research. In general, these platforms belong to knowledge domains which are quite distant from earthquake engineering, and, in general, very costly. The merit of this research effort is that of integrating these very different knowledge domains into an integrated tool capable of responding to very necessary questions related to earthquake resilience of the EUMC network, such as how the operation of the system is impacted by the damage produced by large ground motions. The architecture of the software combines two types of modules, one with simulation capacities, and another with just an I/O smart data capacity. All modules retrieve data from a data lake and are organized by a superior integration layer, also called previously as a middleware, which communicates through a UX designed interface with the web client.

A schematic representation of the dynamics of the problem considered is presented in Figure 2, which shows the high-level interactions between the physical and operational models of the network. The earthquake impact on the EUMC network has two principal expressions, one is the surge in patient demand with very specific pathologies ($d(t),$ most commonly traumatisms), and the second is the physical damage produced on the structures, contents and equipment of these facilities, which leads to a decrease in the instantaneous capacity ($c'(t)$) of the system to provide the intended service. Such deterioration in functionality is recovered in time, and the dynamics of this process also determines the recovery of the operational capacity of the system. The two EUMC networks considered in this study are the SMHCS and the HCSM, both extremely demanded services in the country. Shown in Figure 3 is an image of the topology of the former one, and the geographical layout of the latter. A summary of the types of hospitals and PCUs in each Healthcare Service is presented in Table 1.

3. Description of the simulation platform

We briefly present next some of the principal aspects of each of the network modules, emphasising the more novel components in each case.

3.1. Earthquake hazard (Module 1)

The M1 module is a state-of-art earthquake simulation environment, which allows the characterization of the ground motion intensities (IMs) and their recurrence over a region. The module incorporates several tools used in standard Probabilistic Seismic Hazard Analysis (PSHA), such as the use of decision trees to account for model uncertainties, modern ground motion models, and the computation of exceedance rates at different ground motion levels. In addition, the module features advanced tools to simulate ground motion scenarios for spatially distributed facilities, considering the observed (empirical) correlations of recorded IMs.

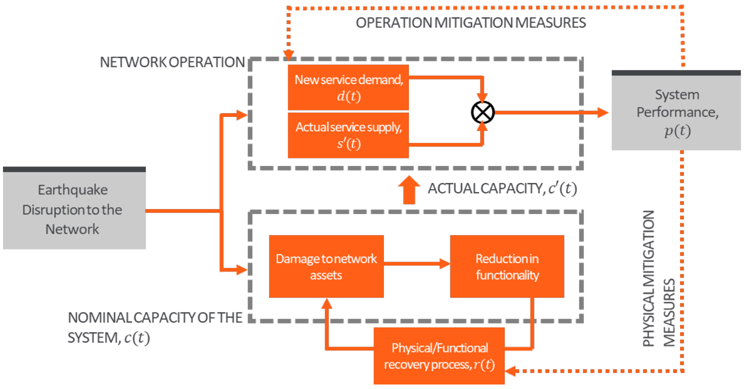
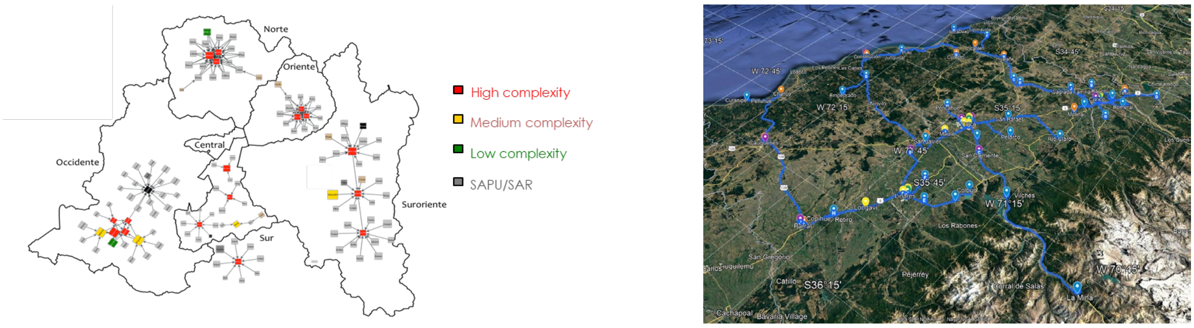


Figure 2 Schematic representation of the dynamics of the EUMC network



(a) (b)

Figure 3 (a) Topology of the Metropolitan healthcare service network identifying the different complexity units; and **(b)** geographical layout and road connectivity of the EUMC Maule network.

Table 1 Hospitals and PCUs in the Healthcare Services under study.

Type of Healthcare Unit	Maule Healthcare Service (HCSM)		Southeast Metropolitan Healthcare Service (SMHCS)	
	Number of facilities	Main structural typology (%)	Number of facilities	Main structural typology (%)
High Complexity Hospital	3	RC (67%)	3	RC Walls (67%), RC MRF (33%)
Medium Complexity Hospital	4	RC (75%)	1	RC Walls (100%)
Low Complexity Hospital	6	Timber and modular steel (67%)	0	-
High Resolutions Emergency Services (SAR)	10	RC (100%)	2	RC Walls (75%), Steel MRF (25%)
Primary Emergency attention service (SAPU)	8	Masonry (75%)	23	RC Walls (70%), Masonry (30%)
Rural emergency service (SUR)	28	Masonry (75%)	0	-

The IMs for each unit in the building inventory are described in terms of 'fields' or 'earthquake scenario maps' of jointly occurring PGA, Sa(0.3) and Sa(1.0) values (i.e., peak ground acceleration and 5% damped pseudo accelerations at 0.3 s and 1.0 s). These maps are later fed into M2 and M4 to simulate the spatial distribution of casualties and network damage. Module 1 has a built-in source model of subduction (Poulos et al. 2019) and shallow crustal (GEM 2020) earthquakes, with their respective magnitude recurrence relations. The mean IM values are obtained from mechanism-specific ground motion models (Bozorgnia et al. 2021; 2014), and a state-of-art VS30 regional model for computing seismic site amplification (Díaz et al. 2022). Similarly, the IM variability across the region takes into account the relative distance between units using appropriate spatial correlations and interperiod correlations models (Aldea, Heresi, y Pastén 2022; Candia et al. 2020), Fig 4.

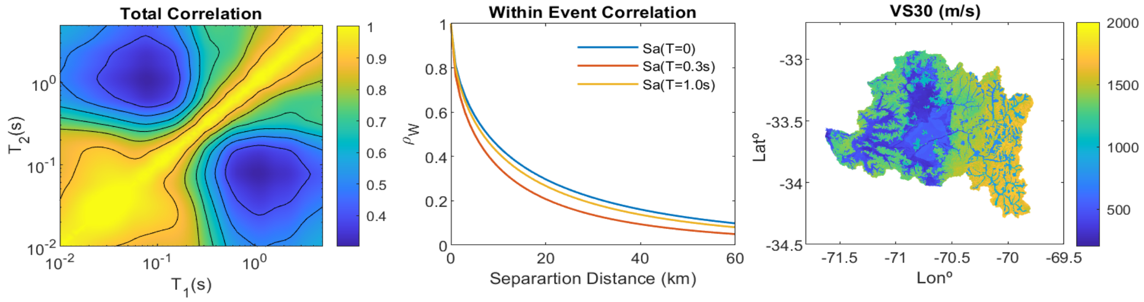


Figure 4 Ground motion correlation models implemented in M1: (left) interperiod correlations for total residuals; (center) spatial correlations for within-event residuals; (right) regional VS30 map based on AI techniques

Earthquake scenario maps can be viewed as a realisation of a multivariate lognormal distribution. This process is implemented in M1 using the extended matrix decomposition (Eq 1), where Y_i (i=1,2,3) are the logarithm of PGA, Sa(0.3) and Sa(1.0), respectively, $\mu_{\log IM_i}$ their mean values, Z_i are independent fields standard normal random values, and L is the positive root of the covariance matrix C, such that LL^{T}=C.

$$\begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} = \begin{bmatrix} \mu_{\log IM_1} \\ \mu_{\log IM_2} \\ \mu_{\log IM_3} \end{bmatrix} + L \begin{bmatrix} Z_1 \\ Z_2 \\ Z_3 \end{bmatrix} \tag{1}$$

Although several thousand IM scenarios result from combining all possible earthquakes and ground motion levels, this number can be significantly reduced. Currently, the M1 hazard module incorporates important sampling techniques and hypocenter clustering to minimise the demand of CPU-time throughout SimPlaNeR.

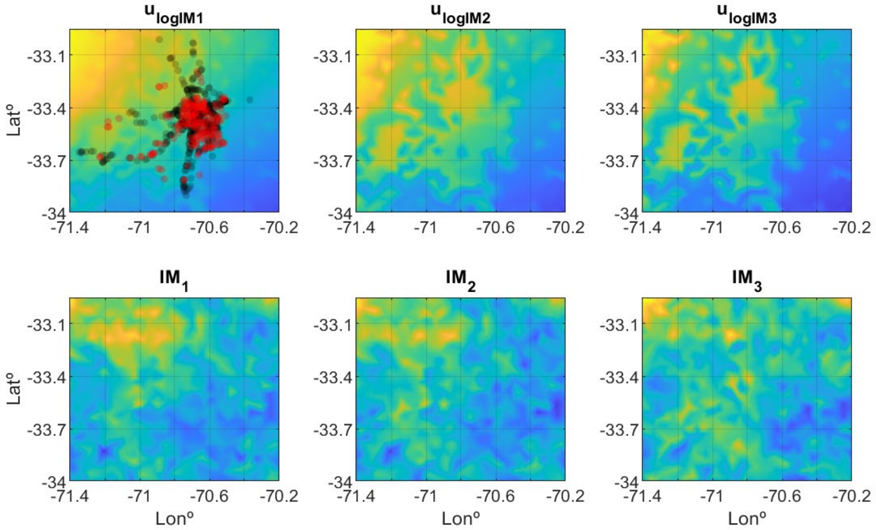


Figure 5 Ground shaking maps for Santiago for a Mw8.7 subduction interface earthquake with focus 80 km offshore La Serena; top row: mean values for 3 intensity measures (IM$_1$=PGA, IM$_2$=Sa0.3 and IM$_3$=Sa1.0); bottom row: spatially cross-correlated random fields. Black circles in the top left figure represent the location of 500 bridges in Santiago, and red circles the location of ~200 healthcare facilities.

A graphical example of earthquake scenario maps for Santiago is shown in Figure 5, for a rectangular 145x145 km grid due to a Mw 8.7 megathrust earthquake with a hypocenter located 400 km NW of Santiago. The first row of plots shows the mean values $\mu_{\log IM_i}$ for each point in the grid; notice that mean intensities increase towards the north-west corner due to smaller site-to-source distances, but also, they increase due to site amplification caused by soft soils (northern Santiago) and deep alluvial deposits (downtown and southern Santiago). The lower row in Figure 5 shows one realisation of the three jointly occurring fields based on Eq. 1, where it is apparent that IMs values are clustered (spatially correlated).

3.2. **City and network exposure model**

Module 2 consists of a set of databases and models (exposure, fragility, and performance) that are used to estimate the distribution of structural damage and casualties across the study region, and ultimately the inflow of patients expected at each PCU and HED for each of the earthquake scenarios generated in M1. Regarding databases, the module provides an exposure model of the urban areas in the Metropolitan and Maule regions, expressed as the number of buildings and the total resident population per structural typology in each census block. The exposure model is referenced to the cartography of the 2017 Chilean census and is based on results presented elsewhere (Santa María et al. 2017), so it accounts only for residential structures that are classified into 18 different building typologies, and for night-time population.

The estimation of earthquake-induced patient arrivals to PCUs and HEDs after a given scenario is completed in four stages. First, the OpenQuake Engine (Pagani et al. 2014) is used to simulate the distribution of structural damage by census block, using the M1 ground shaking maps and the M2 urban exposure model and fragility curves as inputs. Next, the HAZUS casualty model (FEMA 2022) is applied over the damage map to estimate the expected value of the number of casualties with injuries of low, intermediate, and high (critical) severity levels generated at each point. To estimate the resulting demand on each node of the healthcare network, we assume that victims will be directed to the PCU that services their location, if the severity of injuries is low to intermediate, or the closest HED, if they are in critical condition. To reduce time travel calculations, census blocks within a catchment area are clustered based on geographical proximity and damage state.

The exposure model of the healthcare network is stored in M3, as a georeferenced database of all PCUs and HEDs facilities in the SMHCS and Healthcare Service of Maule (HCSM), including attributes such as their structural type, attention capacity, and detailed internal characterization. The hazard input (M1) is used for computing the damage (M4) to the SMHCS and HCSM facilities (M3) and the distribution of injured people in the territory (M2), which will impact the system performance (M5). The SMHCS is located in the capital city, Santiago, and provides healthcare to urban population mostly, with 3 high complexity and 1 medium complexity hospitals, and 25 PCUs. It was considered because it is the largest in the country in terms of associated population (over 1.4 million people), and because it represents the highly interconnected urban network of Santiago, which is served by 6 HCS due to its size (over 6 million people), with important interaction between HCSs in the city and neighbouring regions, such as Valparaíso. To consider this interaction, a high detail model of the urban transportation network of Santiago has been developed, and the effect of bridge seismic damage on ambulance travel times is being studied.

For the case of the HCSM, it suffered extensive damage during the 2010 Maule earthquake (8.8 Mw), due to both, the ground shaking and the subsequent tsunami. Therefore, historical data may exist to validate the platform by including this region. The HCSM serves a population of approximately 1 million people distributed in a surface area of about 30,000 km2, with approximately 55% of the population living in rural or rural-urban areas, and is composed of 59 healthcare centers, with most of them (48) located in the central valley, a minority (10) in coastal areas, and just one in the high mountain area, roughly following the distribution of the population. As summarized in Table 1, the region contains 13 hospitals of different complexity, and 46 PCUs of different types. Generally speaking, the HCSM is divided into three subnetworks (north, central, and south clusters), each one containing one of the High Complexity Hospitals, located in the region largest cities (Curicó, Talca and Linares), some Medium and Low Complexity Hospitals, and several PCUs. The heart of the system is the Hospital in Talca, in the central subnetwork, where the most complex patients are transferred from the entire network. The nodes of the network are distributed in a fishbone-like way (Figure 3b), with a main highway connecting the central valley in the north-south direction, and smaller roads connecting the central valley (mostly the main cities) and the coast in the east-west direction. There is also a north-south road that goes along the coastline. Most of the transportation network redundancy is located in the central valley, which is expected to have an important impact on the system performance if the roads suffer earthquake damage, whenever patients need to be transferred from the coastal cities into the main hospitals in the central valley.

The building typologies include adobe, modular steel, reinforced and confined masonry, timber, and reinforced concrete, with seismic isolation being present in the High Complexity Hospitals. There is high variability among the different buildings in terms of structural layout, particularly for the PCUs given their old age, low complexity, and small associated population; however, the newest PCU units (SARs) built in recent years have capacity for higher complexity patients than other PCUs and are located near important human settlements, so standards have been better defined and are all essentially identical. Module M3 plays a critical role in correctly and efficiently accounting for this variability. A correct characterization of the 29 healthcare centers of the SMHCS and 59 of the HCSM is essential for realistic simulation results of physical damage due to seismic hazard (Module M4), and for calibrating Module M5 to get performance metrics in both the normal and damaged conditions of the system.

3.3. Fragility analysis and performance model

Module M3 also contains a database of fragilities, recovery and cost functions. Data required to compute the performance of the PCUs HEDs uses different levels of information. Each level has been implemented as a specific class in the Python codes developed. The lower level of the system corresponds to components, which include physical resources, and could be structural (e.g. wall, beam, column), architectonical (e.g. ceiling, window), non-architectonical (e.g. clinical gas pipes, lights), and equipment (e.g. magnetic resonance, crash cart). The following level corresponds to capabilities, defined as the set of components required to carry out a medical procedure. The next level includes the rooms, defined as a physical space used to perform a medical procedure. Rooms have different components, which combined, generate a variety of capabilities. The following level are the establishments; a set of rooms that can be physically grouped in one or more buildings, such as a SAR. The final level corresponds to the network, a group of establishments deployed in a geographical location.

A critical input for M3 are the fragility functions of medical equipment. Different studies were reviewed and new empirical fragility functions have been developed based on the observed behavior of medical equipment recently tested in full-scale experiments (Sato et al. 2011; Pantoli et al. 2016; Shi, Kurata, y Nakashima 2014; Guzman Pujols y Ryan 2016). Rolling, sliding, and toppling modes govern the dynamic behavior of wheeled locked, unlocked, and free-standing medical equipment. Recently, experimental responses of the medical equipment deployed in the full-scale, five-story RC building tested at UCSD in 2012 were derived (Guamán-Cabrera, De La Llera, y Mery 2023). In this study, rolling horizontal displacements, rocking, and toppling responses were extracted using the Camera Projection Technique (Hartley R. y Zisserman A 2004). Furthermore, two nonlinear models were proposed to simulate the observed rolling displacement and toppling responses extracted from the CPT (Guamán-Cabrera, De La Llera, y Mery 2023), and correctly validated with experimental data.

By using the calibrated rolling and toppling nonlinear models, analytical Fragility Functions (FFs) were derived for different medical equipment at different locations, support conditions, and orientations. For rolling FFs, horizontal displacements are considered as the damage measure (DM), while for rocking FFs, rocking angles are considered as DM. The collapse state is defined differently for both cases, it depends on proximity to other surrounding objects in rolling and impact forces during collision, while for toppling it depends on the impact force after the rocking angle exceeds the critical rotation angle. As an example, Figure 6a shows the tracking of the unlocked stretcher rolling on the 5th-floor level during the BI-1: CNP100 motion, while Figure 6b displays the rocking FF of the locked stretcher subjected to the FB-4: ICA100 motion using the 2D toppling model.

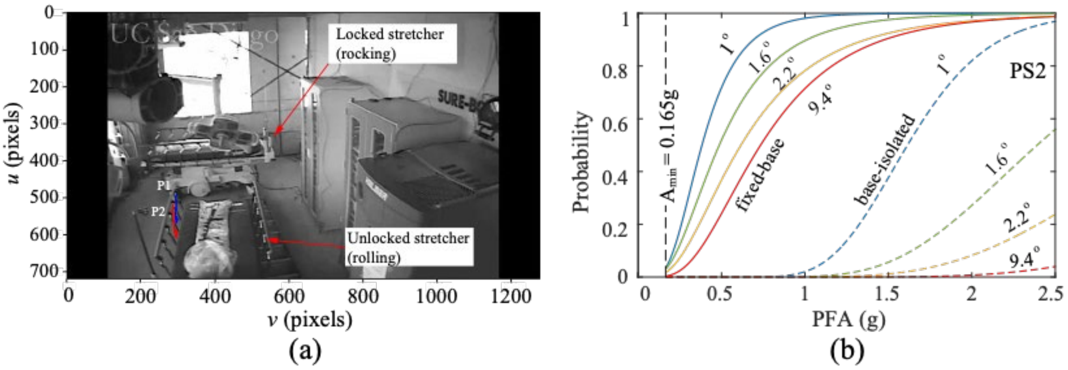


Figure 6 a) tracking of unlocked stretcher using the Camera Projection Technique (CPT); **b)** rocking fragility curve of locked stretcher for fixed and base-isolated conditions.

Module M4 contains the performance model used to analyze the physical response of the network. First, the collapse of each establishment is evaluated using the seismic hazard and collapse FFs. If there is no collapse, the physical performance of each establishment is evaluated using simplified structural models (FEMA 2018), such as plane uncoupled linear models, or a surrogate lognormal distribution model fitted with results of several nonlinear response history analyses. Taking IMs given by M1, different engineering demand parameters (EDPs) are estimated at different locations of each structure, such as peak floor accelerations and inter-story drifts. The damage state of each component is estimated considering FFs and the previously computed EDPs. Recovery time and costs are estimated for each component using the recovery functions, and logic tree models that relate the capability functionality with the damage state of its components determine the recovery times of the former. An example of a recovery function is shown in Figure 7 at the establishment aggregation level.

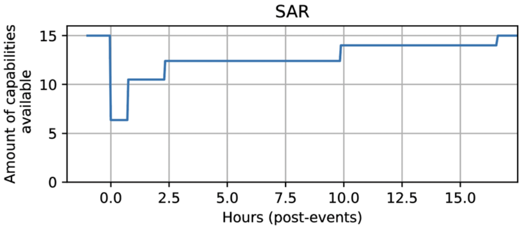


Figure 7 Example of a recovery curve for all the capabilities of a SAR.

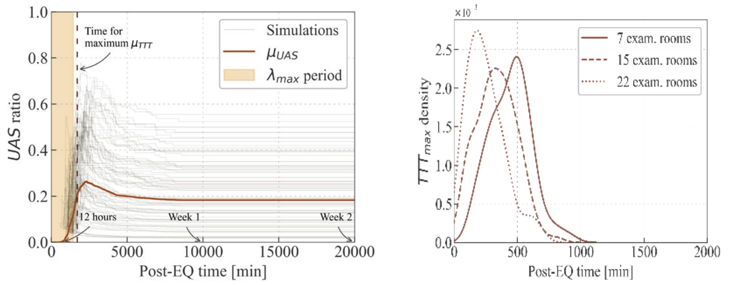


Figure 8 Simulation results for two weeks after the earthquake: **a)** Determination of mean UAS curves for ED-level patients with minor injuries; **b)** Impact of changes in available ERs (examination rooms) on the PDFs of maximum TTT obtained after Monte Carlo simulations.

3.4. Patient flow simulation

Discrete Event Simulation (DES) is commonly used in the study of healthcare systems (Günal y Pidd 2010; Fone et al. 2003). However, during the last decade, the attempts to model hospital system processes have decreased (Gunal y Pidd 2007) as a result of the challenge to accurately represent the complexity of hospital processes and activities. Achieving an appropriate simplification of this activity can be an exceedingly intricate process. The types of facilities considered are based on resolution capacity, i.e. High-Resolution PCUs (SAR), PCUs (SAPU), and HEDs. We consider the following events as state-changing events in the system: (1) patient arrival; (2) patient discharge; (3) start of use of resources; (4) end of use of resources; (5) patient transfer from one healthcare facility to another; and (6) transfer patient arrival. It is important to note that the simulation aims to replicate the behaviour of the system in normal and post-seismic event conditions. A novel aspect in the simulation is that it takes into account the increased demand on the emergency services and includes the actual capacity that is gradually restored in the aftermath of the event.

Patients with different healthcare needs arrive at each facility according to a non-homogeneous Poisson process with a known rate. After arrival, patients are triaged based on severity, and depending on the category, they are prioritised on a waiting list. Once the healthcare requirement is determined and severity is assessed, the patient waits for treatment at the same facility or may be referred to another. Referrals occur when the facility does not have the capacity to deal with the patient's healthcare condition. The patient is transported in an ambulance. The medical resources required to provide treatment for each potential healthcare requirement are known. Resources are split into treatment rooms and peripheral services (e.g. sample testing, radiology, hospital beds).

An initial simplified model considering typical earthquake-related patient paths have been used to get a first estimate of the earthquake impact on the medical resource requirements at HEDs. The model includes a DES of simplified medical processes delivered during the surge in demand of patient profiles after the earthquake. Empirical data from the literature in disaster medicine and expert elicitation of emergency healthcare staff defined the required attention processes. Different patients within the ED define different paths for the different profiles. For instance, the path for a trauma patient with crush syndrome includes healthcare processes, such as: triage, initial examination, laboratory services, surgery, intensive care, dialysis, and recovery hospitalization. Arriving patients were studied as an inflow of injured agents, which are divided into groups denoted as patient types (Merino-Peña et al. 2023), accounting for earthquake-related injuries and illnesses ranging from frequent trauma conditions to stress-related ischemic conditions. Patient types and healthcare paths were matched using an extensive literature review on medical processes of past earthquakes and specialized knowledge from emergency physicians. A time-varying patient arrival function was assumed for the rate of patients at the ED during the first week after the earthquake. Every process is linked to a list of resources that include the area where the service is performed (room) and its duration. Medical services considered cover specialized processes at tertiary hospitals including but not limited to HEDs.

We defined performance metrics to assess the hospital response such as patient's time-to-treatment (TTT) and the ratio between unassisted-patients and total arriving patients of every group (UAS). The effect of the increase in HED capacity was evaluated for two weeks after the earthquake. The simulated scenarios represent the effect of additional service areas and the loss in capacity due to any malfunction after the earthquake. Mean curves of the UAS ratio were determined from Monte Carlo simulations for each patient type. It is apparent that the UAS ratio is zero during the first 12 hours as the TTT values have not exceeded the time threshold used for ED patients with no surgery requirements (Figure 8a). Distributions of maximum values of TTT versus time and their mean values, μ_{TTTmax} vary with the change in ER resources are presented in Figure 8b. If the simplified model is applied to a case-study hospital, it was found that maximum TTT for ED-level patients could increase up to 40% if the functional examination rooms (ERs) decrease to half. We also found that the use of medical resources is highly governed by the emergency processes defined to respond to the surge in patient arrivals.

3.5. **Network planning**

A model is proposed for the optimal selection of network planning measures based on their impact on the healthcare provided after the earthquake. The objective is to choose an optimal set of actions from a cost-benefit analysis point of view, encompassing both ex-ante and ex-post decisions. The selection of an optimal portfolio includes the uncertainty of the problem reflected in the damage that system experiences during the event, the surge in demand for emergency healthcare, the possibility of post-event recovery actions (recourse), and the interactions between different network systems, among other effects. From a modeling perspective, these aspects are incorporated into a two-stage coupled stochastic optimization problem, a widely used tool in optimization problems under uncertainty (Birge y Louveaux 2011). First stage decisions consider options such as seismic retrofit, seismic upgrade and redundancy. In the second stage, measures such as the installation of field hospitals, and increase in medical resources are considered. The optimization model is defined as follows:

$$
\begin{aligned}
z^* = \text{mín} \;\; & \sum_{i=1}^{I}\sum_{j=1}^{J} x_{ij}\, c_{ij} + \mathbb{E}_{\omega_1,\omega_2}[Q(x,\omega)] \\
\text{s.a.} \;\; & \sum_{j=1}^{J} x_{ij} \leq 1 \\
& x \in \{0,1\},\; i = 1,\cdots,I,\; j = 1,\cdots,J \\
Q(x,\omega) = \text{mín} \;\; & \mathbb{E}_{\omega_3}[C(y, F_1(\omega_1), F_2(x,\omega_1,\omega_2),\omega_3)] + y^t h \\
\text{s.a.} \;\; & \sum_{\ell=1}^{L} y_\ell \leq 1 \\
& y_\ell \in \{0,1\},\; \ell = 1,\cdots,L
\end{aligned}
\tag{2}
$$

Figure 9 Stabilization of the optimal solution with increasing number of simulations

where y_l is a binary variable indicating whether a field hospital is installed at location l, and h_l is its associated cost; x_{ij} is a binary variable indicating whether retrofit j is applied to hospital i, and c_{ij} is its associated cost. The cost function C represents the expected quality of service of the system post event. This function depends on both first- and second-stage variables, as well as the random variables ω_1, ω_2, and ω_3, which represents the ground motion intensities (M1), the variability in the remaining capacity of health centers, and the variability in the simulator, respectively. The expected value in the objective function is approximated using the Sample Average Approximation Technique (Rubinstein y Shapiro 1990). Additionally, the functions F_1 and F_2 represent the number of injured individuals and the remaining capacity of health centers, respectively.

Based on M5, a neural network is trained to predict the average patient waiting time, based on the input of the C function. This network is incorporated into the optimization model using a modern functionality of the Gurobi solver based on the JANOS framework (Bergman et al. 2022).The framework allows for the integration of decision variables as inputs and outputs of the neural network, which are modeled with a mixed-integer programming formulation. In Figure 9, an example with 80 scenarios is presented. The optimal value of the model becomes stable reaching a relatively low variability (represented by the orange-colored area).

3.6. **Risk analysis (Module 6)**

The selection of an optimal portfolio of preparation and mitigation measures requires analysing a large number of seismic scenarios to account for uncertainties in the ground motions, building response, medical treatment times, etc. For each realization, a set of output variables is obtained from modules 1 through 5, which characterize the system's performance. Given an output variable OV, all realizations are combined using the risk framework represented by Eq. (3) (Poulos, de la Llera, y Mitrani-Reiser 2017), which leads to results that may be interpreted in terms of the mean annual rate of exceedance of an output variable.

$$\lambda_{OV}(ov) = \int_{im_{min}}^{\infty} P(OV \geq ov \mid IM = im) |d\lambda_{IM}(im)| \tag{3}$$

where IM is a seismic intensity measure; im_{min} is the largest IM value that has no engineering significance; $\lambda_X(x)$ is the mean annual frequency of random variable X exceeding a value x; λ_{IM} is the hazard curve; and $P(OV \geq ov \mid IM = im)$ is the probability of output variable OV exceeding a value ov, given the occurrence of a seismic event with $IM = im$. A Poisson recurrence model is assumed for OV, thus $\lambda_X(x) = \nu P(X \geq x)$, where ν is the mean annual rate of significant events. We use this relationship to estimate the risk curve λ_{OV} from the numerical results of the Monte Carlo simulation. Thus, the probability of exceedance $P(OV \geq ov)$ is estimated, and then this value is used to compute λ_{OV}. The estimation of $P(OV \geq ov)$ is numerical and considers any variance reduction technique, such as Importance Sampling (Jayaram y Baker 2010):

$$\hat{P}(OV \geq ov) = \sum_{i=1}^{N_r} I(OV_i \geq ov)\Lambda_i \;/ \sum_{i=1}^{N_r} \Lambda_i \tag{4}$$

where $\hat{P}(OV \geq ov)$ is the estimate of OV exceeding value ov; $I(OV_i \geq ov)$ is an indicator function which equals 1 if $OV_i \geq ov$ and 0 otherwise; and Λ_i is the Importance Sampling weight of realization $i = 1, \ldots, N_r$. Module 6 has been implemented to efficiently run the Monte Carlo simulations, and to postprocess the results as explained above, for both single and multiple output variables. Output variables from M5 are processed and M6 metrics are sent to M7, which optimize the selection of a portfolio of preparedness and mitigation strategies.

4. Data for the two actual healthcare services

Data plays a fundamental role in this project and field visits to HEDs and PCUs in Santiago and Maule have been carried out, which include a detailed characterization of the emergency department critical rooms (e.g., observation, medical treatment, reanimation rooms), the support services (e.g., blood bank, sterilization, X rays), and the lifeline services (e.g., water, electric power, telecommunications). All visits have included at least one professional of the medical facility guiding it and explaining important aspects of the physical and operational dimension of the spaces. Data has been provided by the HCS including detailed inventories and characterizations of physical assets (e.g., number of beds, autonomy of water tanks) and human resources (e.g., number of nurses and shifts), structural and architectural plans of the buildings, network operational rules, emergency protocols, among others. Databases describing the emergency admissions and characterization of patients have also been provided. The data has gone through very complex protocols to ensure anonymity. So far, all emergency admissions of 2022 for the HCSM have been collected, which comprises slightly more than two million admissions, and data for the previous seven years is currently being processed, while data for the MSEHCS is expected to be provided soon. Each admission is described by 99 variables. This data allow to roughly measure the transfer of patients through the network, as well as to assess which medical conditions lead to longer stays in the system or are associated with more difficult assessment. Since module M5 requires high resolution data for patient attention times, data will be complemented with interviews to medical personnel to obtain realistic patient archetypes, the associated sequence of medical processes, and their required resources.

5. Discussion and conclusions

It becomes apparent that the capacity of performing an integrated systemic analysis of the physical and operational responses of the EUMC network subject to a large earthquake, would significantly contribute to a better management of these services. Currently, there is no tool available to anticipate the healthcare consequences of future emergencies that lead to a sudden deterioration in the capacity of medical care concurrently with a surge in the number of patients. This simultaneous action of the two factors may lead to serious consequences in the capacity to offer healthcare. This statement, however, is somewhat speculative since these services have demonstrated in the recent past with the Covid-19 pandemic a tremendous adaptation capacity. However, such adaptation occurred in longer time windows rather than in a sudden episode as the one produced by a large earthquake. Consequently, and under these conditions, it is likely that the response of the HCS could be significantly improved at different levels with a risk analysis and planning tool such as SimPlaNeR.

The development of this integrated model and software has enabled us to identify a large number of research gaps. The most significant are: (i) a more sophisticated and (experimentally) validated casualty generation model; (ii) fragility functions associated with HED capacities (rooms) rather than fragilities of isolated structural, non-structural, and medical equipment components; (iii) more comprehensive fragility functions of medical equipment; (iv) better models to translate structural, non-structural and equipment damage into functional consequences; (v) a validated model for patient flows in the HED and PCU units, which recognizes the archetypes of ailments most common to earthquake patients; (vi) a clear identification between the patient archetypes and the medical resources needed to treat these patients; and (vii) the capacity to discriminate between different possible actions to improve the resilience of the healthcare network by intervening the assets before and after the earthquake.

Although there are still significant assumptions at the different stages of modelling in SimPlaNeR, current technologies are not capable of responding questions that this platform will enable us to respond. For instance, one of the basic research questions that motivated this study was to evaluate the practical healthcare implications of the use of seismic isolation technologies in hospital designs. Currently, the decisions are typically made on economic reasons exclusively, with little or no information of the true performance of the network. The implications in terms of operation continuity of a seismically isolated structure have never been studied from the overall network performance perspective. How important is it to include seismic isolation in a given hospital? or is it not? Moreover, if relevant, what are the implications of using seismic isolation in terms of variables that are relevant to decision makers and the health of people? This software has been specifically designed and developed for healthcare networks, and as such it is intended to respond very specific questions that may help in the management of the network. The seismic isolation question is just an example, since we could incorporate other questions as well regarding physical or operational interventions and evaluate their impact in terms of risk.

Perhaps, one of the most novel parts of this research and development is the construction of the module for planning the healthcare network under a framework of uncertainty. This is an incredibly complex problem of stochastic optimization, and surrogate models of the patient flows are needed for allowing the treatment using the real dimensions of the problem. The optimization algorithm proposed in two stages is also very useful for the decision maker since the nature of the interventions are different before and after the earthquake. Running this optimization problem on top of the complex stochastic simulation of the network is a significant achievement of this research. So far this has been tested only with synthetic data and the real proof will come when we use the true healthcare databases. This module provides information that is essentially impossible to have currently in the system, and hence, will support medium and long terms decisions to improve network resilience.

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7. References

Aldea, Sofía, Pablo Heresi, y César Pastén. 2022. “Within-event Spatial Correlation of Peak Ground Acceleration and Spectral Pseudo-acceleration Ordinates in the Chilean Subduction Zone”. *Earthquake Engineering & Structural Dynamics* 51 (11): 2575–90. https://doi.org/10.1002/eqe.3674.

Bergman, David, Teng Huang, Philip Brooks, Andrea Lodi, y Arvind U. Raghunathan. 2022. “JANOS: An Integrated Predictive and Prescriptive Modeling Framework”. *INFORMS Journal on Computing* 34 (2): 807–16. https://doi.org/10.1287/ijoc.2020.1023.

Birge, John R., y François Louveaux. 2011. *Introduction to Stochastic Programming*. Springer Series in Operations Research and Financial Engineering. New York, NY: Springer New York. https://doi.org/10.1007/978-1-4614-0237-4.

Bozorgnia, Yousef, Norman A Abrahamson, Sean K Ahdi, Timothy D Ancheta, Linda Al Atik, Ralph J Archuleta, Gail M Atkinson, et al. 2021. “NGA-Subduction Research Program”. *Earthquake Spectra*, diciembre, 875529302110560. https://doi.org/10.1177/87552930211056081.

Bozorgnia, Yousef, Norman A. Abrahamson, Linda Al Atik, Timothy D. Ancheta, Gail M. Atkinson, Jack W. Baker, Annemarie Baltay, et al. 2014. “NGA-West2 Research Project”. *Earthquake Spectra* 30 (3): 973–87. https://doi.org/10.1193/072113EQS209M.

Candia, Gabriel, Alan Poulos, Juan Carlos de la Llera, Jorge G.F. Crempien, y Jorge Macedo. 2020. “Correlations of Spectral Accelerations in the Chilean Subduction Zone”. *Earthquake Spectra* 36 (2): 788–805. https://doi.org/10.1177/8755293019891723.

Díaz, J.P., E. Sáez, M. Monsalve, G. Candia, F. Aron, y G. González. 2022. “Machine Learning Techniques for Estimating Seismic Site Amplification in the Santiago Basin, Chile”. *Engineering Geology* 306 (septiembre): 106764. https://doi.org/10.1016/j.enggeo.2022.106764.

FEMA. 2018. “P-58: Seismic Performance Assessment of Buildings. Volume 1 - Methology”. https://femap58.atcouncil.org/documents/fema-p-58/24-fema-p-58-volume-1-methodology-second-edition.

———. 2022. “Hazus Earthquake Model Technical Manual”. https://www.fema.gov/flood-maps/tools-resources/flood-map-products/hazus/user-technical-manuals.

FlexSim. 2023. “FlexSim Healthcare”. *FlexSim* (blog). 2023. https://www.flexsim.com/healthcare/.

Fone, D., S. Hollinghurst, M. Temple, A. Round, N. Lester, A. Weightman, K. Roberts, E. Coyle, G. Bevan, y S. Palmer. 2003. “Systematic Review of the Use and Value of Computer Simulation Modelling in Population Health and Health Care Delivery”. *Journal of Public Health* 25 (4): 325–35. https://doi.org/10.1093/pubmed/fdg075.

GEM. 2020. “GEM Global active fault viewer”. 2020. https://blogs.openquake.org/hazard/global-active-fault-viewer (2020).

Guamán-Cabrera, Jaime, Juan Carlos De La Llera, y Domingo Mery. 2023. “Seismic Performance Assessment of Medical Equipment Using Experimentally Validated Rolling and Toppling Nonlinear Models”. *Earthquake Spectra*, julio, 87552930231180904. https://doi.org/10.1177/87552930231180904.

Gul, Muhammet, y Ali Fuat Guneri. 2015. “Simulation modelling of a patient surge in an emergency department under disaster conditions”. *Croatian Operational Research Review* 6 (2): 429–43. https://doi.org/10.17535/crorr.2015.0033.

Günal, M M, y M Pidd. 2010. “Discrete Event Simulation for Performance Modelling in Health Care: A Review of the Literature”. *Journal of Simulation* 4 (1): 42–51. https://doi.org/10.1057/jos.2009.25.

Gunal, Murat M., y Michael Pidd. 2007. “Interconnected DES models of emergency, outpatient, and inpatient departments of a hospital”. En *2007 Winter Simulation Conference*, 1461–66. Washington, DC, USA: IEEE. https://doi.org/10.1109/WSC.2007.4419757.

Guzman Pujols, Jean C., y Keri L. Ryan. 2016. “Development of Generalized Fragility Functions for Seismically Induced Content Disruption”. *Earthquake Spectra* 32 (3): 1303–24. https://doi.org/10.1193/081814EQS130M.

Hartley R. y Zisserman A. 2004. *Multiple View Geometry in Computer Vision*. 2nd edition. Cambridge: Cambridge University Press.

Jayaram, Nirmal, y Jack W. Baker. 2010. “Efficient Sampling and Data Reduction Techniques for Probabilistic Seismic Lifeline Risk Assessment”. *Earthquake Engineering & Structural Dynamics*, n/a-n/a. https://doi.org/10.1002/eqe.988.

Merino-Peña, Yvonne, Luis Ceferino, Sebastian Pizarro, y Juan Carlos De La Llera. 2023. “MODELING HOSPITAL RESOURCES BASED ON GLOBAL EPIDEMIOLOGY AFTER EARTHQUAKE-RELATED DISASTERS”. Preprint. https://doi.org/10.31224/3238.

Pagani, M., D. Monelli, G. Weatherill, L. Danciu, H. Crowley, V. Silva, P. Henshaw, et al. 2014. “OpenQuake Engine: An Open Hazard (and Risk) Software for the Global Earthquake Model”. *Seismological Research Letters* 85 (3): 692–702. https://doi.org/10.1785/0220130087.

Pantoli, Elide, Michelle C. Chen, Xiang Wang, Rodrigo Astroza, Hamed Ebrahimian, Tara C. Hutchinson, Joel P. Conte, et al. 2016. “Full-Scale Structural and Nonstructural Building System Performance during Earthquakes: Part II – NCS Damage States”. *Earthquake Spectra* 32 (2): 771–94. https://doi.org/10.1193/012414eqs017m.

Pegden, Claude Dennis. 2023. “Healthcare Simulation and Scheduling Software | Simio”. 2023. https://www.simio.com/applications/healthcare-simulation-software/.

Poulos, Alan, Juan Carlos de la Llera, y Judith Mitrani-Reiser. 2017. “Earthquake Risk Assessment of Buildings Accounting for Human Evacuation: EARTHQUAKE RISK ASSESSMENT OF BUILDINGS ACCOUNTING FOR EVACUATION”. *Earthquake Engineering & Structural Dynamics* 46 (4): 561–83. https://doi.org/10.1002/eqe.2803.

Poulos, Alan, Mauricio Monsalve, Natalia Zamora, y Juan C. de la Llera. 2019. “An Updated Recurrence Model for Chilean Subduction Seismicity and Statistical Validation of Its Poisson Nature”. *Bulletin of the Seismological Society of America* 109 (1): 66–74. https://doi.org/10.1785/0120170160.

Rubinstein, Reuven Y., y Alexander Shapiro. 1990. “Optimization of Static Simulation Models by the Score Function Method”. *Mathematics and Computers in Simulation* 32 (4): 373–92. https://doi.org/10.1016/0378-4754(90)90142-6.

Santa María, Hernán, Matías A. Hube, Felipe Rivera, Catalina Yepes-Estrada, y Jairo A. Valcárcel. 2017. “Development of National and Local Exposure Models of Residential Structures in Chile”. *Natural Hazards* 86 (S1): 55–79. https://doi.org/10.1007/s11069-016-2518-3.

Sato, Eiji, Sachi Furukawa, Atsuo Kakehi, y Masayoshi Nakashima. 2011. “Full-scale Shaking Table Test for Examination of Safety and Functionality of Base-isolated Medical Facilities”. *Earthquake Engineering & Structural Dynamics* 40 (13): 1435–53. https://doi.org/10.1002/eqe.1097.

Shi, Yundong, Masahiro Kurata, y Masayoshi Nakashima. 2014. “Disorder and Damage of Base-isolated Medical Facilities When Subjected to Near-fault and Long-period Ground Motions”. *Earthquake Engineering & Structural Dynamics* 43 (11): 1683–1701. https://doi.org/10.1002/eqe.2417.