Structure and Infrastructure Engineering
Vol. 6, Nos. 1–2, February–April 2010, 127–144

Seismic resilience of a hospital system

Gian Paolo Cimellaro[a]*, Andrei M. Reinhorn[b] and Michel Bruneau[b]

[a]*Department of Structural & Geotechnical Engineering (DISTR), Politecnico di Torino, Room 7, Corso Duca degli Abruzzi 24, 10129, Turin, Italy;* [b]*Department of Civil, Structural and Environmental Engineering,University at Buffalo, The State University of New York, 212 Ketter Hall, Buffalo, NY 14260, USA*

(*Received 25 October 2007; final version received 3 December 2008*)

This paper presents a comprehensive model to quantify disaster resilience of systems that is defined as the capability to sustain functionality and recover from losses generated by extreme events. The model combines loss estimation and recovery models and can be applied to critical facilities (e.g. hospitals, military buildings, etc.), as well as utility lifelines (e.g. electric power systems, transportation networks, water systems etc.) that are crucial to the response of recovery processes, decisions and policies. Current research trend leads toward the definition of complex recovery models that are able to describe the process over time and the spatial definition of recovery (e.g. meta-models for the case of health care facilities). The model has been applied to a network of hospitals in Memphis, Tennessee. The resilience framework can be used as a decision support tool to increase the resilience index of systems, such as health care facilities, and reduce disaster vulnerability and consequences.

Keywords: fragility; functionality; hospital; losses; recovery; resilience

1. Introduction

Hospitals constitute an important part of the health-care system. During a disaster, their role is even more critical; therefore, it is vital to provide timely and good quality treatment to injured patients in order to minimise fatalities (Viti *et al.* 2006). Hospital performance estimates (before and during an extreme event) can assist disaster mitigation efforts to provide timely treatment to the injured and ill, so it is essential to provide a performance measure that will eventually be used by policy makers.

According to the terminology of the Multidisciplinary Center for Earthquake Engineering Research (MCEER), the performance of a hospital (or system) during a disaster is measured using a unique decision variable (DV), defined as resilience, which combines other variables (economic losses, casualties, recovery time, etc.) that are usually employed to judge performance during extreme events. As described by Bruneau *et al.* (2003), resilience has been defined as the ability of a system to reduce the chances of a shock, to absorb such a shock if it occurs and to recover quickly after a shock. The resilience is defined using a mathematical function describing the serviceability of the system, which is described here as functionality. Graphically, the resilience is defined as the normalised shaded area underneath the functionality $Q(t)$ of a system. The parameter $Q(t)$ is a non-stationary stochastic process, and each ensemble is a piecewise continuous function as the one shown in Figure 1 (all parameters in Figure 1 have been defined in the text below Equation (2)), where the functionality $Q(t)$ is measured as a non-dimensional (percentage) function of time. Specifically, $Q(t)$ ranges from 0 to 100%, where 100% means no reduction in performance, while 0% means total loss. In particular, if an earthquake occurs at time t_{NE}, it could cause sufficient damage to the infrastructure such that the performance $Q(t)$, is immediately reduced (Figure 1).

Mathematically, for a single event, resilience is defined by the following equation (Bruneau *et al.* 2004, 2007):

$$r_i = \int_{t_{0E}}^{t_{0E}+T_{\mathrm{RE}}} Q(t)\ \mathrm{d}t, \tag{1}$$

where t is the time, t_{0E} is the initial time of the extreme event E, functionality is defined as (Cimellaro *et al.* 2006a, 2009a):

$$Q(t) = 1 - L(I, T_{\mathrm{RE}})[H(t - t_{0E}) - H(t - (t_{0E} + T_{\mathrm{RE}}))]\ f_{\mathrm{rec}}(t, t_{0E}, T_{\mathrm{RE}}), \tag{2}$$

*Corresponding author. Email: gpc2@buffalo.edu

ISSN 1573-2479 print/ISSN 1744-8980 online

DOI: 10.1080/15732470802663847
http://www.informaworld.com

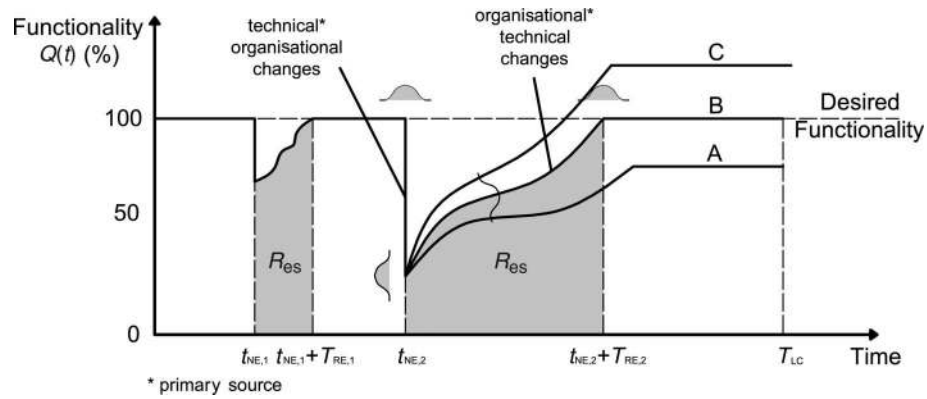

Figure 1. Schematic representation of seismic resilience.

where I is the earthquake intensity, $L(I,\ T_{\mathrm{RE}})$ is the loss function; f_{rec} $(t,\ t_{0E},\ T_{\mathrm{RE}})$ is the recovery function; $H(t_0)$ is the Heaviside step function; T_{RE} is the recovery time from event E; and t_{NE} is the time of occurrence of event E. This is a possible definition of functionality of a system where a clear distinction is made between immediate losses L and recovery f_{rec}. However, users can adopt another type of functionality $Q(t)$ that better describes the problem at hand. For example, for a single hospital system, a measure of functionality is given in Equation (8), while a different type of functionality is adopted for a hospital network in Equation (10).

2. Uncertainties in seismic resilience

The quantification of seismic resilience at the physical level proceeds through a probabilistic framework because of the considerable uncertainties in the field of earthquake and extreme-event engineering in both demand and capacity. The system diagram in Figure 2 identifies the key steps of the framework to quantify resilience, highlighting the uncertain variables inside the framework (intensity parameters (I), response parameters (R), performance measures (PM), etc.). The reader is referred to Cimellaro *et al.* (2009a) for more information on the MCEER assessment methodology.

Analytically, when uncertainties are considered in Equation (1), the expression of resilience becomes:

$$\bar{R} = \sum_{T_{\mathrm{RE}}}^{N_{T_{\mathrm{RE}}}} \sum_{L}^{N_L} \sum_{\mathrm{PM}}^{N_{\mathrm{PM}}} \sum_{R}^{N_R} \sum_{i}^{N_{i*}} r_i\ P(T_{\mathrm{RE}}|L)\ P(L|\mathrm{PM})\ P(\mathrm{PM}|R)$$
$$P(R|I)\ P(I_{T_{\mathrm{EC}}} > i^*)\ \Delta I\ \Delta R\ \Delta\mathrm{PM}\ \Delta L\ \Delta T_{\mathrm{RE}}, \quad (3)$$

where r_i is given in Equation (1) with the kernel shown in Equation (2), while the six sources of uncertainties are: (i) intensity measures I; (ii) response parameters R; (iii) performance threshold r_{lim}; (iv) performance measures PM; (v) losses L; and (vi) recovery time T_{RE}. The conditional probabilities in Equation (3) considering the various uncertainties are: $P(I_{T_{\mathrm{LC}}} > i^*)$, the probability of exceeding a given ground motion parameter i^* in a time period T_{LC}; $P(R|I)$ reflecting the uncertainties in the structural analysis (demand) parameters, i.e. uncertainties of the structural parameters and uncertainties of the model itself; $P(PM|R)$ describes the uncertainties in the estimation of performance limit states; $P(L|PM)$ describes the uncertainties in the loss estimation, while $P(T_{\mathrm{RE}}|L)$ describes the uncertainties in the time of recovery. Note that the range of parameters with uncertain quantities has been divided into discrete steps in Equation (3).

The methodology that is summarised in Equation (3) is more general than that proposed by Cimellaro *et al.* (2005), because in that framework, only the uncertainties of the intensity measure I were considered, whereas in this framework, all other uncertainties are involved.

Although Blockley (1999) stated that probabilistic structural reliability calculations can only provide partial evidence in the process of assessing and managing the safety of structures, the probabilistic framework proposed here is found to be effective to address the problem of quantifying concepts such as resilience and functionality. The model presented is comprehensive; however, the methodology was just illustrated through a case study, including a network of hospital facilities and its components. It focuses mainly on seismic resilience for the sake of simplicity, although the present concepts and formulations are equally applicable to other type of hazards.

3. The four properties of resilience

Resilience consists of the following properties:

Rapidity: the capacity to meet priorities and achieve goals in a timely manner in order to contain losses, recover functionality and avoid future disruption. Mathematically, it represents the slope of the functionality curve (Figure 3a) during the recovery time, and can be expressed by the following equation:

$$\text{Rapidity} = \frac{\mathrm{d}Q(t)}{\mathrm{d}t}, \quad \text{for } t_{0E} \le t \le t_{0E} + T_{\mathrm{RE}}. \quad (4)$$

An average estimation of rapidity can be defined by knowing the total losses and the total recovery time to again reach 100% functionality:

$$\text{Rapidity} = \frac{L}{T_{\mathrm{RE}}} (\text{average recovery rate in percentage/time}), \quad (5)$$

where L is the loss, or the drop of functionality, right after the extreme event.

Robustness: strength, or the ability of elements, systems and other measures of analysis to withstand a given level of stress or demand, without suffering degradation or loss of function. It is therefore the residual functionality right after the extreme event (Figure 3b) and can be represented by:

$$\text{Robustness } (\%) = 1 - L(m_L, \sigma_L), \quad (6)$$

where L is a random variable expressed as a function of the mean m_L and the standard deviation σ_L. A more explicit definition of robustness is obtained when the dispersion of the losses is expressed directly:

$$\text{Robustness } (\%) = 1 - L(m_L + a\sigma_L), \quad (7)$$

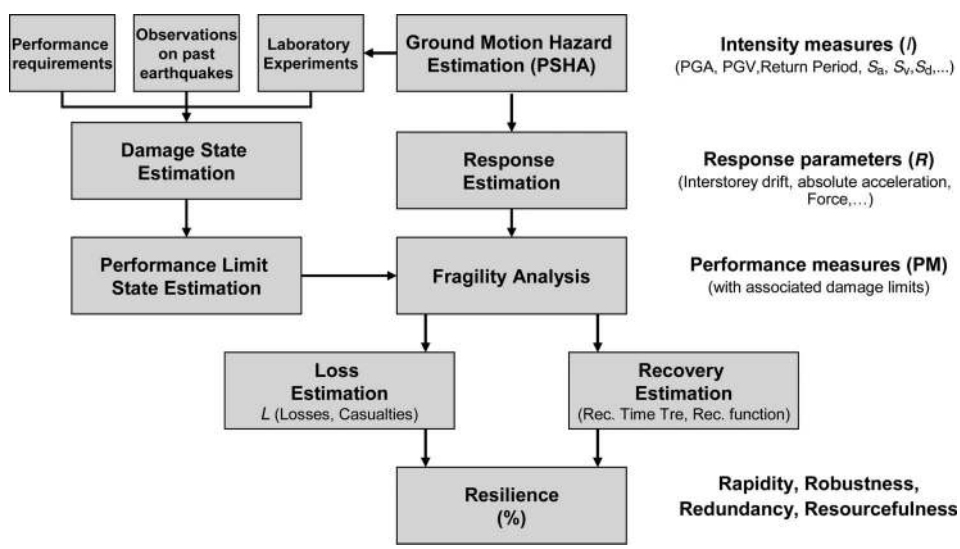

Figure 2. Performance assessment methodology (MCEER approach) (Cimellaro *et al.* 2009a)

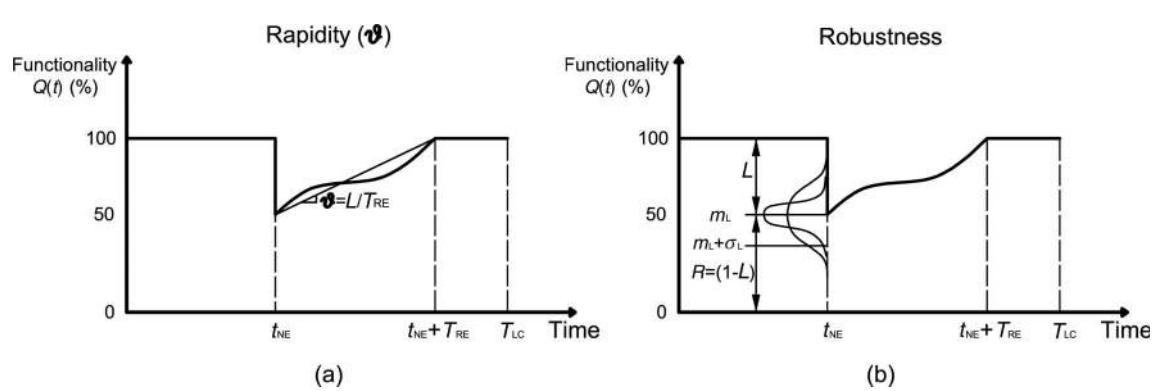

Figure 3. Dimensions of resilience: (a) rapidity and (b) robustness.

where a is a multiplier of the standard deviation corresponding to a specific level of losses. A possible way to increase uncertainty in robustness of the system is to reduce the dispersion in the losses represented by σ_L. In this definition, robustness reliability is therefore also the capacity of keeping variability of losses within a narrow band, independently of the event itself. Two examples of systems with and without robustness are, respectively, the Emergency Operation Center (EOC) and the Office of Emergency Management (OEM) organisation during the World Trade Center (WTC) disaster in 2001 (Kendra and Wachtendorf 2003). The EOC facility (part of the OEM), was not sufficiently robust to survive the 11 September attack (as it was located on the 23rd floor of the 7 WTC). However, on the strength of its resourcefulness (see below), OEM exhibited considerable robustness as an organisation, demonstrating an ability to continue to function, even after losing its WTC facility and a great part of its communications and information technology infrastructure. When the latter was restored, it contributed to the resilience of the OEM as a functional and effective organisational network.

Redundancy: is the extent to which alternative elements, systems or other measures exist, that are substitutable, i.e. capable of satisfying functional requirements in the event of disruption, degradation or loss of functionality. The mathematical formulation of the alternative redundant systems and measures is simplistic and beyond the scope of this paper.

Resourcefulness: is the capacity to identify problems, establish priorities and mobilise alternative external resources when conditions exist that threaten to disrupt some element, system or other measure. Resourcefulness can be further conceptualised as consisting of the ability to apply material (i.e. monetary, physical, technological and informational) and human resources in the process of recovery to meet established priorities and achieve goals. Resourcefulness is primarily an ad-hoc action, which requires momentary decisions to engage additional and alternative resources. Its quantification is better illustrated graphically.

In order to explain the meaning of these two last properties, namely resourcefulness (Figure 4) and redundancy (Figure 5), graphical developments are shown using the expanded three and four dimensions of Figure 1.

In Figure 4, a third axis illustrates that added resources can be used to reduce time to recovery. In theory, if infinite resources were available, time to recovery would asymptotically approach zero, but

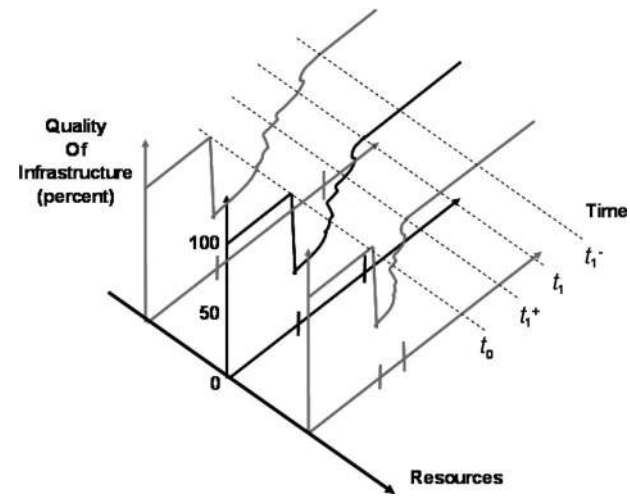

Figure 4. Expansion of resilience in the resourcefulness dimension.

practically, even in the presence of enormous financial and labour capabilities, human limitations will dictate a practical minimum time to recovery. In fact, even in a resourceful society, the time to recovery after a disaster may be significantly longer than necessary due to adequate planning, organisational failures/inadequacies or ineffective policies. On the contrary, in a less technology advanced society, where resources are scarce, time to recovery lengthens, approaching infinity in the absence of any resources.

Figure 5 illustrates redundancy, the fourth dimension of resilience, by grouping multiple plots of the type shown in Figure 4 that could represent the resilience of a single hospital. Figure 5 presents the resilience of all acute care facilities over a geographical area. However, it is important to note that lifelines (e.g. highway and street network, bridges, etc.), which provide linkages among geographically distributed hospitals, also play a role in the definition of global regional resilience and add another layer of complexity. This will be the object of future studies, as it requires knowledge of the fragility of the transportation network. In this paper, it is assumed that the performance of a network of hospitals can be established by simple aggregation of the performance of individual facilities.

Resourcefulness and redundancy are strongly coupled, but difficult to quantify, because they depend on human factors and available resources; therefore, an analytical function is not provided for these two quantities at this stage. However, changes of resourcefulness and redundancy affect the shape and the slope of the recovery curve, the recovery time T_{RE}, and they also affect rapidity and robustness. It is through redundancy and resourcefulness (as means of

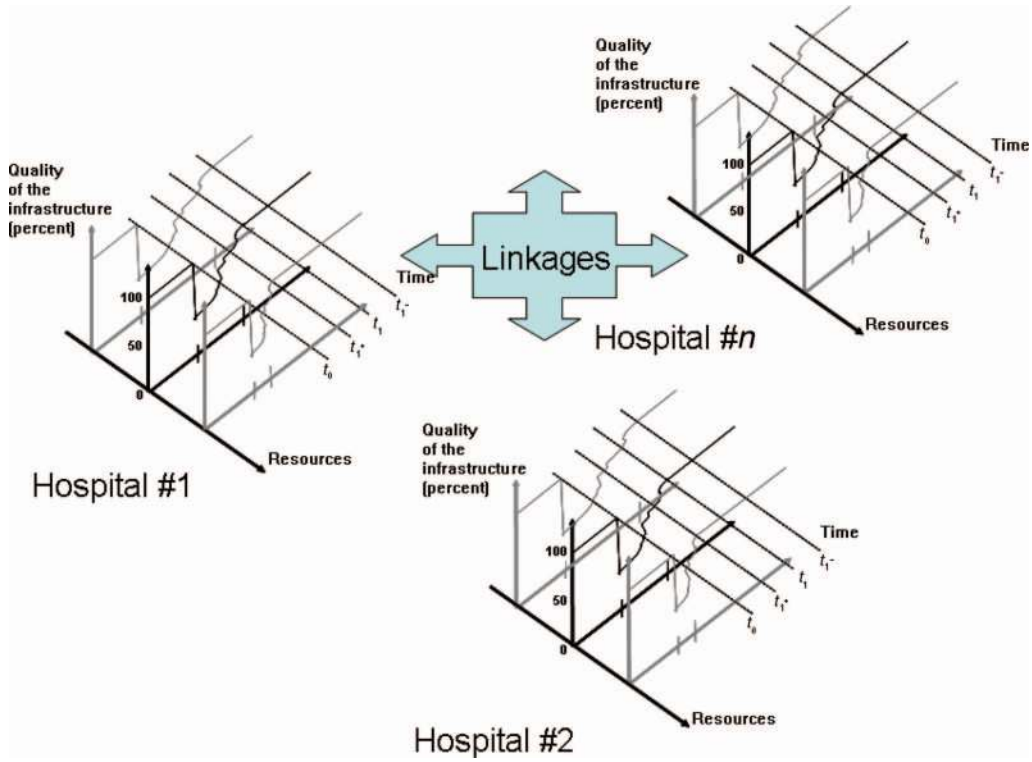

Figure 5. Expansion of resilience in the redundancy dimension.

resilience) that the rapidity and robustness (the ends of resilience) of an entire system can be improved. Resilience will still be a function of these four quantities (strongly coupled), but while the influence of robustness and rapidity is clear, the influence of resourcefulness and redundancy is more complex.

4. Resilience of a hospital

Residents in seismic area have expressed their strong expectation that acute care facilities be available and operational following an earthquake (Alexander 1996). The state of California has already taken steps in that direction by enacting ordinance SB1953, which requires that acute care facilities be retrofitted by 2030 to a level that would allow them to be fully operational following an earthquake (Alesch and Petak 2004).

The vertical axis of Figure 1 is very difficult to define and quantify for certain types of critical facilities (e.g. acute care facilities), since the functionality $Q(t)$ cannot be defined in very simple engineering units, such as for power grids or water distribution networks, where simple and quantifiable units, such as kilowatts or litres, can be used. Functionality can be measured and defined in various ways according to the problem at hand. However, common sense, and also a relevant literature review reported in various references (Maxwell 1984, McCarthy *et al.* 2000, Vieth and Rhodes 2006) indicate that functionality of a hospital can be defined in terms of quality of service (QS). Therefore, if a measure of QS is found, then it is possible to measure the functionality Q of the health care facility.

Vieth and Rhodes (2006) found that the quality of care is affected by the level of crowding in the emergency room (ER), which is directly related to the waiting time (WT), that a patient needing assistance spends in the queue before receiving it. Furthermore, McCarthy *et al.* (2000) identified the waiting time as an indicator of quality of service.

In this case, functionality is expressed by the following equations, where functionality is defined as normalised waiting time and a distinction between the waiting time before and after the critical condition is made:

$$Q(t)=\begin{cases} Q_1(t)=\dfrac{\max((WT_{\text{crit}}-WT_0)-WT,0)}{WT_{\text{crit}}-WT_0}, WT<WT_{\text{crit}}, \\ Q_2(t)=\dfrac{WT_{\text{crit}}-WT_0}{\max(WT_{\text{crit}},WT-(WT_{\text{crit}}-WT_0))}, WT\geq WT_{\text{crit}}, \end{cases} \tag{8}$$

where WT_{crit} is the waiting time at the maximum capacity of the hospital; WT_0 is the waiting time in the normal operational conditions pre-disaster; and WT is the waiting time during the transient condition. The resilience can be obtained according to the following equation:

$$R = \alpha \int_{T_{\text{LC}}} \frac{Q_1(t)}{T_{\text{LC}}} \mathrm{d}t + (1-\alpha) \int_{T_{\text{LC}}} \frac{Q_2(t)}{T_{\text{LC}}} \mathrm{d}t, \quad (9)$$

where α is a weighting factor used to combine the integral of the two functionalities defined above and T_{LC} is the control time of the system.

5. Resilience of a hospital network

At the *community level* (e.g. when hospitals over a geographical area are considered), a measure of functionality could be defined as the quality of life expressed as a percentage of healthy population during the extreme event, normalised with respect to the total healthy population before that event:

$$Q(t) = \begin{cases} Q_1(t) = \dfrac{\max((N_{WT\text{crit}} - N_{WT0}) - N_{WT}, 0)}{N_{WT\text{crit}} - N_{WT0}}, \\ N_{WT} < N_{WT\text{crit}}, \\ Q_2(t) = \dfrac{N_{\text{crit}} - N_{\text{W0}}}{\max(N_{\text{crit}}, N_{WT} - (N_{\text{crit}} - N_{WT0}))}, \\ N_{WT} \geq N_{WT\text{crit}}, \end{cases} \quad (10)$$

where $N_{WT\text{crit}}$ is the number of people waiting needing assistance at the maximum capacity of the hospital; N_{WT0} is the number of people waiting for assistance in the normal operational pre disaster conditions; and N_{WT} is the number of people waiting during the transient conditions. Equations (8) and Equations (10) are equivalent when the normalised percentage of waiting time can be directly correlated to the percentage of healthy population and used a measure of functionality at the community level. In both cases, the resilience is evaluated using Equation (9).

The first drop in the size of the healthy population would occur when individuals are killed by seismically deficient structures, or from other causes, during an earthquake (Peak-Asa *et al.* 1998). At the community level, this drop will not change whether hospitals are seismically retrofitted or not, except for those deaths that would occur in seismically deficient hospitals. This could be a significant global societal measure of functionality for an entire community (not just a hospital) and can be used for policy making; however, it suffers a number of shortcomings. First, the quantification of unhealthy versus healthy population may be difficult (although not impossible). Second, establishing how many deaths the earthquake directly, or indirectly, caused could be a challenge. Third, the definition of the relevant geographical boundaries can be problematic given that the wealthier and mobile segment of the population may find its health needs answered in other places (states or countries).

6. Improvements of resilience

As shown in Figure 6, a first interim improvement of resilience is possible at the technical dimension level, by reducing the immediate physical losses right after an earthquake. However, socio-economic information has to be collected in order to generate the knowledge base for the organisational dimension and to translate the functionality of the system into operational consequences, in order to adapt, and mathematically change, the recovery function in Equation (3). Figure 6 shows also the necessity of the fragility of non-structural building components to achieve the research objectives through the probabilistic framework described in this paper. Achieving a given target seismic resilience for acute care facilities requires the harmonisation of the performance levels between structural and non-structural components. Even if the structural components of a hospital building achieve an immediate occupancy performance level after a seismic event, failure of architectural, mechanical or electrical components of the building can lower the seismic resilience of the entire building system. Furthermore, the investment in non-structural components and building contents for the hospital is far greater than that of structural components and framing (Taghavi and Miranda 2003). Therefore, the development of equipment fragility (which is usually responsibility of industry) is most urgent. Availability of such calibrated and reliable data, integrated into a decision support system that would model the dependencies illustrated in Figure 6 would allow decision makers to achieve reliable decisions based on optimisation of resources targeted to enhance seismic resilience of an existing hospital or ensemble of geographically distributed facilities.

7. Loss estimation

The evaluation of resilience first requires a loss estimation model, as shown in Equation (2), and, in

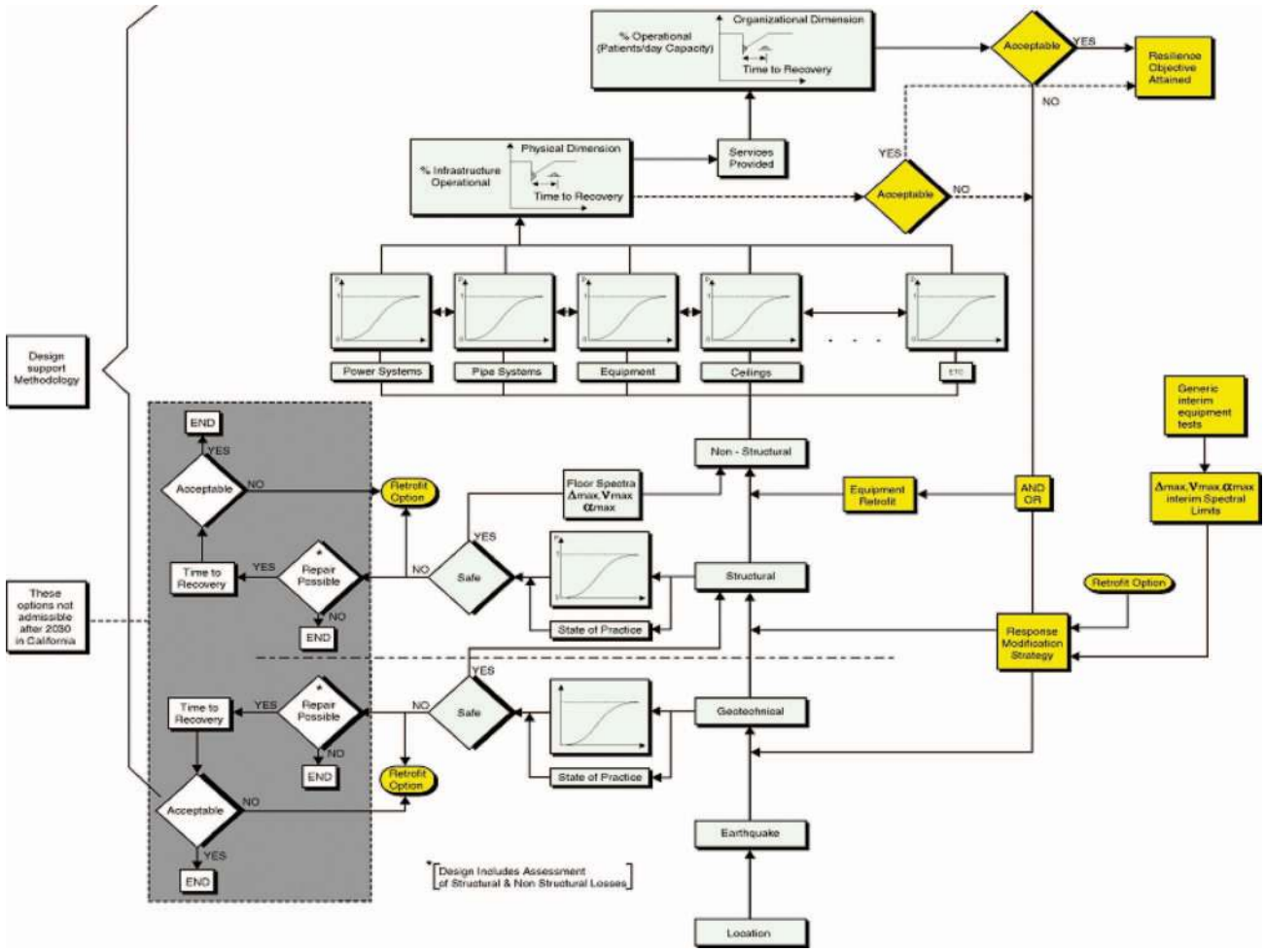

Figure 6. Flow chart of the procedure to achieve seismic resilience for a single hospital.

particular, damage descriptors that can be translated into either monetary terms or other units, which can be measured or counted, e.g. the number of people requiring hospitalisation. The loss estimation procedure is by itself a source of uncertainty, and this is taken into account in Equation (3). Users of the resilience model can adopt the proposed framework, but they can substitute their preferred methodology to estimate the losses, L (NRC 1992, Coburn *et al.* 2002, Okuyama *et al.* 2004) to use in Equations (1–2) for evaluating the resilience of systems.

8. Simplified recovery function model

Most of the models available in the literature, including the PEER equation framework (Cornell and Krawinkler 2000), are loss estimation models that focus on initial losses caused by disaster, where losses are measured relative to pre-disaster conditions. However, none of the aforementioned literature addresses the temporal dimension of post-disaster loss recovery. As indicated in Figure 1, the recovery time T_{RE} and the recovery path are essential for evaluating resilience, so they should be estimated accurately. Unfortunately, most common loss models, such as HAZUS (Whitman *et al.* 1997) evaluate the recovery time in crude terms and assume that, within one year, everything returns to normal. However, as shown in Figure 1, the system considered may not necessary return to the pre-disaster baseline performance. It may exceed the initial performance (Figure 1, curve C), when the recovery process ends, in particular when the system (e.g. community, essential facility, etc.) may use the opportunity to fix pre-existing problems inside the system itself. On the other hand, the system may suffer permanent losses and equilibrate below the baseline performance (Figure 1, curve A).

These considerations show that the recovery process is complex and is influenced by time dimensions, spatial dimensions (e.g. different neighbourhoods may have different recovery paths) and by interdependencies between different economic sectors that are involved in the recovery process. Therefore, different critical facilities (e.g. hospitals), which belong to the same community but are located in different neighbourhoods, have different recovery paths and, in some (mainly poor) areas, these essential facilities may experience long-term or permanent damage (Chang 2000). In summary, the recovery process shows disparities among different geographic regions in the same community, showing different rates and quality of recovery. Modelling recovery of a single critical facility or of an entire community is a complex subject (Cimellaro *et al.* 2009b). These two processes cannot be assumed independent, although they are presented in two separate paragraphs in this paper for the sake of simplicity.

Information on comprehensive models that describe the recovery process is very limited. Miles and Chang (2006) set out the foundations for developing models of community recovery, presenting a comprehensive conceptual model and discussing some related issues. Once these complex recovery models are available, it is possible to describe relationships across different scales, socio-economic agents, neighbourhood and community, and to study the effects of different policies and management plans in an accurate way. In this paper, the recovery process is oversimplified using recovery functions that can fit the more accurate results obtained with the Miles and Chang (2006) model.

Different types of recovery functions can be selected depending on the system and society preparedness response. Three possible recovery functions are shown in Equation (11) below: (i) linear, (ii) exponential (Kafali and Grigoriu 2005) and (iii) trigonometric (Chang and Shinozuka 2004):

$$\text{linear: } f_{\text{rec}}(t, T_{\text{RE}}) = \left(1 - \frac{t - t_{0E}}{T_{\text{RE}}}\right);$$

$$\text{exponential: } f_{\text{rec}}(t) = \exp[-(t - t_{0\text{E}})(\ln 200)/T_{\text{RE}}]; \text{ and}$$

$$\text{trigonometric: } f_{\text{rec}}(t) = 0.5\{1 + \cos[\pi(t - t_{0E})/T_{\text{RE}}]\}. \tag{11}$$

The simplest form is a linear recovery function that is generally used when there is no information regarding the preparedness, resources available and societal response (Figure 7a). The exponential recovery function may be used where the societal response is driven by an initial inflow of resources, but then the rapidity of recovery decreases as the process nears its end (Figure 7b). The trigonometric recovery function can be used when the societal response and the recovery are driven by lack or limited organisation and/or resources. As soon as the community organises itself, sometimes with the help of other communities, then the recovery system starts, while the rapidity of recovery increases (Figure 7c). Such recovery occurred after Nisqually Earthquake (Filiatrault *et al.* 2001, Park *et al.* 2006).

9. Recovery model for health care facilities (metamodel)

Due to the complexity of a hospital's organisational operations during a disaster, a hybrid simulation combined with analytical modelling, also called a metamodel is used for the description of the dynamic behaviour of the hospital system during the transient state.

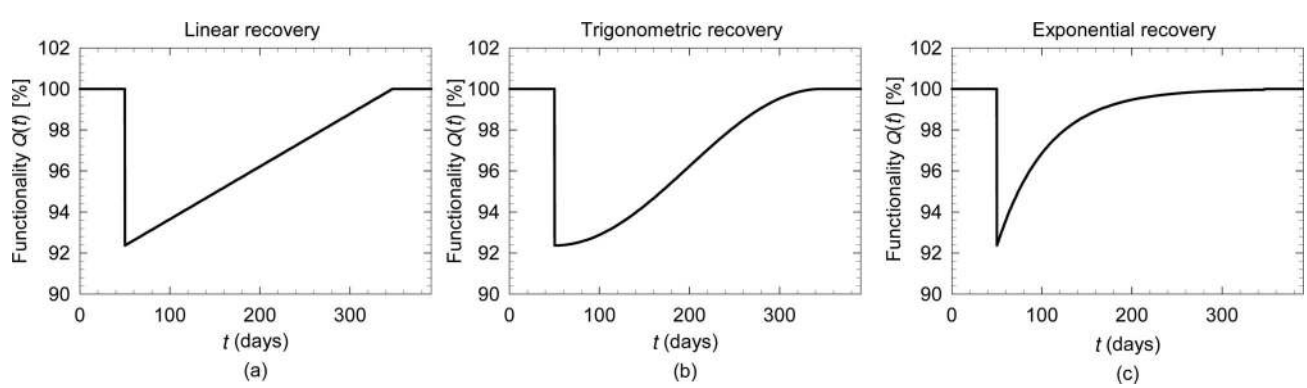

Figure 7. Functionality curves: (a) average-prepared community, (b) not well-prepared community and (c) well-prepared community.

The transient modelling approach, using simulation and a double exponential function (Paul *et al.* 2006), is adopted for this case. The variables used in the metamodel for the description of the organisational hospital system are: (i) the number of beds available in the hospital (B), (ii) the number of operating rooms (OR) and (iii) the efficiency of utilisation (E), defined as the number of surgeries per operating room per day (Figure 8). The input of the metamodel includes the arrival rate λ of the patients at the hospital and the partial mix α, defined as a percentage of number of patients requiring an operating room. The parameters of the metamodel are calibrated using regressions obtained by output of designated simulation experiments (Figure 8).

As a result of the hybrid simulation, the metamodel produces the patient waiting time WT, which is used in Equation (8) as an aggregated measure of functionality $Q(t)$ of the hospital, which is further used to calculate the resilience in Equation (9), according to the flow chart in Figure 8.

When uncertainties are considered the resilience r_i is defined as the normalised area underneath the function $Q(t)$ that describes the functionality of the system (Bruneau *et al.* 2003, Cimellaro *et al.* 2006a,b, Bruneau and Reinhorn 2007):

$$r(WT_{\text{crit}}, \alpha, \lambda, I) = \int_{t_{0E}}^{t_{0E}+T_{\text{LC}}} Q(t)/T_{\text{LC}}\mathrm{d}t, \qquad (12)$$

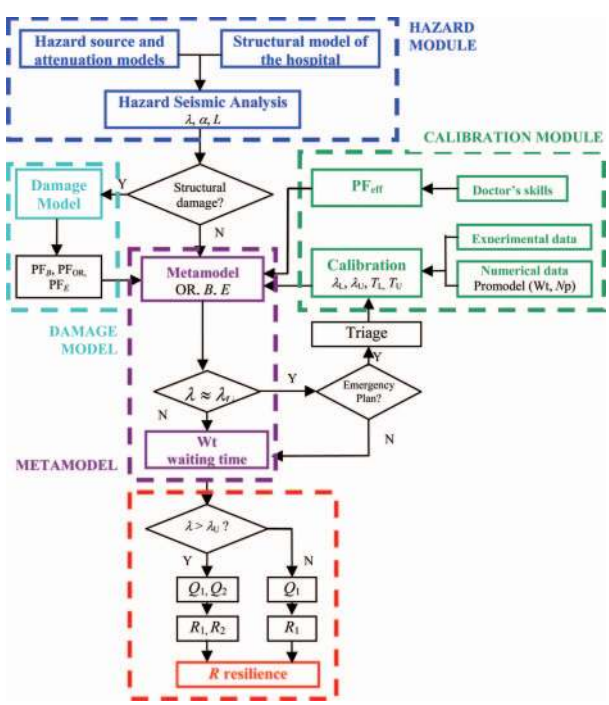

Figure 8. Flow chart of a single hospital metamodel.

where WT_{crit}, α, λ and I are random variables defining the survivability time, the partial patient mix, the arrival rate and the intensity measure of the earthquake, respectively, while $Q(t)$ is given by the combination of Q_1 and Q_2 in Equation (10). Therefore, the resilience is a function of a random variable containing the four jointly distributed random variables.

The formulation is compatible with the one provided in Equation (3), when α, λ and I are grouped as intensity measures (I), while WT is used to define the performance measure (PM) of the hospital. The formulation at the community level, however, is using α and λ explicitly as response measures (R). The most important expectation moment, which describes the random variable defining the resilience, is the first moment, called simply mean or expectation and is defined as:

$$m_r = E(r) = \int_I \int_\lambda \int_\alpha \int_{WT_{\text{crit}}} r(WT_{\text{crit}}, \alpha, \lambda, I) f_{WT_{\text{crit}}\alpha\lambda I} \, \mathrm{d}WT_{\text{crit}}\mathrm{d}\alpha \, \mathrm{d}\lambda \, \mathrm{d}I, \qquad (13)$$

where $f_{WT_{\text{crit}}\alpha\lambda I}$ is the joint probability density function (jpdf) of the four random variables defined above, which are not independent. Therefore, in this case, it is simpler to determine the jpdf as a function of the conditional probability density functions as:

$$f_{WT_{\text{crit}}\alpha\lambda I} = f(WT_{\text{crit}}|\alpha, \lambda, I) f(\alpha|\lambda, I) f(\lambda|I) f(I). \qquad (14)$$

Besides the mean, the other most important moment is the variance, which measures the dispersion of the four random variables, r about its mean and is defined as:

$$\mu_2 = \sigma_r = E\left\{(r - m_r)^2\right\} = \int_I \int_\lambda \int_\alpha \int_{WT_{\text{crit}}} (r(WT_{\text{crit}}, \alpha, \lambda, I) - m_r)^2 f_{WT_{\text{crit}}\alpha\lambda I} \, \mathrm{d}WT_{\text{crit}}\mathrm{d}\alpha \, \mathrm{d}\lambda \, \mathrm{d}I. \qquad (15)$$

A dimensionless function, defining the coefficient of variation υ_r, is used to characterise the dispersion with respect to the mean:

$$\upsilon_r = \frac{\sigma_r}{m_r}. \qquad (16)$$

The formulation of resilience given in Equations (13)–(15) includes only the uncertainties in the operations

due to the earthquake input variables, while it is assumed that the organisational behaviour of the hospital is not affected by the physical structural damages that may happen in the hospital itself.

In the general case, when physical structural damages are also considered, three more random variables describing the organisational system of the hospital are taken into account: the number of operating rooms OR, the number of beds B and the efficiency E. Therefore, the jpdf becomes:

$$\begin{aligned} f_{WT_{\text{crit}}\alpha\lambda IEB\text{OR}} = {} & f(\text{OR}|D,\text{PM},R,I)f(B|D,\text{PM},R,I) \\ & f(E|D,\text{PM},R,I)f(D|\text{PM},R,I)f(\text{PM}|R,I) \\ & f(R|I)f(WT_{\text{crit}}|\alpha,\lambda,I)f(\alpha|\lambda,I)f(\lambda|I)f(I) \end{aligned} \tag{17}$$

where D is a damage measure. The mean and the variance of resilience, when physical structural damage is included, are given by the following expressions that are evaluated numerically:

$$\begin{aligned} m_r = E(r) = {} & \int_I \int_\lambda \int_\alpha \int_{WT_{\text{crit}}} \int_{\text{OR}} \int_B \int_E \\ & r(WT_{\text{crit}},\alpha,\lambda,I,\text{OR},B,E)\, f_{WT_{\text{crit}}\alpha\lambda IEB\text{OR}} \\ & \text{d}\text{OR}\text{d}B\text{d}E\text{d}WT_{\text{crit}}\text{d}\alpha\,\text{d}\lambda\,\text{d}I \end{aligned} \tag{18}$$

and

$$\begin{aligned} \sigma^2 &= E\left\{(r-m_r)^2\right\} \\ &= \int_I \int_\lambda \int_\alpha \int_{WT_{\text{crit}}} \int_{\text{OR}} \int_B \int_E (r(WT_{\text{crit}},\alpha,\lambda,I)-m_r)^2 \\ & \quad f_{WT_{\text{crit}}\alpha\lambda IEB\text{OR}}\text{d}\text{OR}\text{d}B\text{d}E\text{d}WT_{\text{crit}}\text{d}\alpha\text{d}\lambda\text{d}I. \end{aligned} \tag{19}$$

The probability that resilience r is smaller than a specified critical value r_{crit}, for the case when structural damage is included in the model, is defined as:

$$\begin{aligned} P(r \le r_{\text{crit}}) = {} & \int_I \int_\lambda \int_\alpha \int_{WT_{\text{crit}}} \int_{\text{OR}} \int_B \int_E f_{WT_{\text{crit}}\alpha\lambda IEB\text{OR}} \\ & \text{d}\text{OR}\text{d}B\text{d}E\text{d}WT_{\text{crit}}\text{d}\alpha\text{d}\lambda\text{d}I. \end{aligned} \tag{20}$$

10. Fragility function

The calculation of seismic resilience based on loss of functionality, particularly related to the physical structural damages (see Equation (2)), makes use of the fragility functions, or the conditional probability of exceeding the limit states. Fragility curves are functions that represents the probability that the response $\boldsymbol{R} = \{R_1, \ldots, R_n\}$ of a specific structure (or family of structures) exceeds a given performance threshold $\boldsymbol{r}_{\text{lim}} = \{r_{\text{lim}1}, \ldots, r_{\text{lim}n}\}$, associated with a performance limit state, conditional on earthquake intensity parameter I, such as the peak ground acceleration (pga), peak ground velocity (pgv), return period, spectral acceleration (S_{a}), spectral displacements (S_{d}), modified Mercalli intensity (MMI), etc. The response $\boldsymbol{R}$ and the limit states $\boldsymbol{r}_{\text{lim}}$ are expressions of the same variable (or measure) such as deformation, drift, acceleration, stresses, strains, (mechanical characteristics) or other functionality measures.

The response $\boldsymbol{R}$ and response threshold $\mathbf{r}_{\text{lim}}$ are functions of the structural properties of the system $\mathbf{x}$, the ground motion intensity I and the time t. However, in this formulation, it is assumed that the response threshold $\boldsymbol{r}_{\text{lim}}(\boldsymbol{x})$ does not depend on the ground motion history and so does not depend on time, while the demand $R_i(\mathbf{x},I,t)$ of the generic ith component is replaced by its maximum value over the duration of the response history $R_i(\mathbf{x},I)$. The dependence of the response $\boldsymbol{R}(\mathbf{x},I)$ on $\mathbf{x}$ and I, and the dependence of the response threshold $\boldsymbol{r}_{\text{lim}}(\mathbf{x})$ on $\mathbf{x}$ will be omitted in the following for sake of simplicity.

Based on the above assumptions, the multi-parameter n, the definition of fragility F, (identical to the $P(PM|R)$) can be written in the following form (Cimellaro *et al.* 2006b):

$$\begin{aligned} P(\text{PM}|R) = F &= P\left\{\bigcup_{i=1}^{n}(R_i \ge r_{\text{lim}\,i})\right\} \\ &= \sum_i P\left\{\bigcup_{i=1}^{n}(R_i \ge r_{\text{lim}\,i})|I=i\right\}P(I=i), \end{aligned} \tag{21}$$

where R_i is the response parameter related to a certain measure (deformation, force, velocity, etc.) and $r_{\text{lim}i}$ is the response threshold parameter correlated with the performance level. The definition of fragility in Equation (21) requires implicitly the definition of the performance limit states $\boldsymbol{r}_{\text{lim}}$.

The calculation of fragility is performed using a generalised formula describing the multi-dimensional performance limit state threshold (MPLT), and it allows the consideration of multiple limit states related to different quantities in the same formulation (Cimellaro *et al.* 2006b, Cimellaro and Reinhorn 2009). The multi-dimensional performance limit state function $L(r_{\text{lim}1}, \ldots, r_{\text{lim}n})$ for the n-dimensional case,

when n different types of limit states are considered simultaneously, can be given by:

$$L(\mathbf{r}_{\lim}) = \sum_{i=1}^{n} \left(\frac{r_{i\lim}}{r_{i\lim,0}} \right)^{N_i} - 1, \qquad (22)$$

where $r_{i\lim}$ is the dependent response threshold parameter (deformation, force, velocity, etc.) that is correlated with damage; $r_{i\lim,0}$ is the independent capacity threshold parameter; and N_i are the interaction factors determining the shape of the n-dimensional surface. This model can be used to determine the fragility curve of a single non-structural component, or to obtain the overall fragility curve for the entire building including its non-structural components. Such a function allows the inclusion of different mechanical response parameters (force, displacement, velocity, accelerations, etc.) and combines them together in a unique fragility curve. Different limit states can be modelled as deterministic or random variables, and they can be considered either linear, nonlinear dependent or independent using the desired choice of the parameters appearing in Equation (22). For example in a three-dimensional non-dimensional space, when the multi-dimensional performance threshold considers only three response parameters, Equation (22) assumes the shape, as shown in Figure 9. More details about the methodology for evaluating fragility are given in Cimellaro *et al.* 2006b.

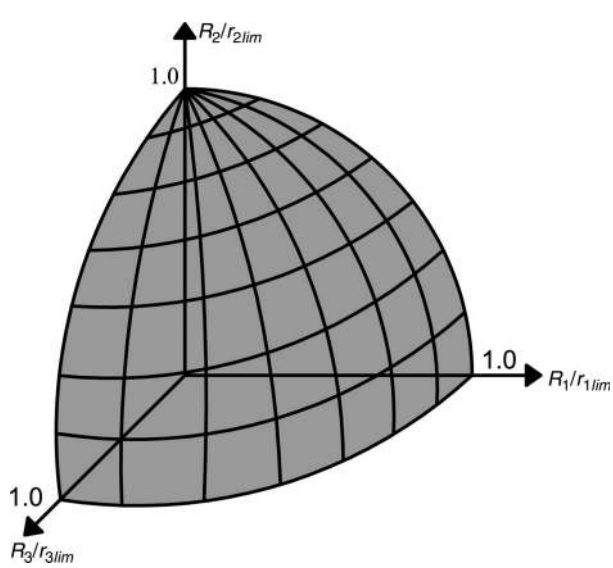

Figure 9. Multi-dimensional threshold performance limits (Cimellaro *et al.* 2006b).

11. Case study of hospital network

The selected example is a regional loss estimation study that evaluates the economic losses of a network of six hospital buildings within a geographical region, such as the city of Memphis, Tennessee (in this case). The response of buildings was estimated using an equivalent linearisation spectral capacity method as presented by Reinhorn *et al.* (2001), similar to the procedure described in HAZUS. The limit states were expressed in terms of median and log-standard deviation, chosen according to the building type and the design code (FEMA 2005).

Figure 10 shows the locations (by latitude and longitude) and the structural type of the hospitals (based on Park *et al.* 2004). The location information is used to define the seismic hazard (USGS 2002), and the structural types are used to define the seismic vulnerability (FEMA 2005). The first four hospitals are mid-rise buildings with concrete shear walls (C2M as per the HAZUS classification), the fifth is a low-rise building with unreinforced masonry bearing walls (URML) and the sixth is a low-rise building with concrete shear walls (C2L) (Table 1).

Alternative retrofit actions are selected as defined in FEMA 276 (1999) and directly correlated to the HAZUS code levels. Therefore, the HAZUS code levels are assigned as performance measures (PM) to the retrofit strategies mentioned above with the following assumptions: (i) it is assumed that the no action option, corresponds to the low code level, (ii) the retrofit to life safety level option is assumed to be a moderate code level and (iii) the retrofit to immediate occupancy level option is assumed to be a high code level. For the rebuild option, a special high code level is assumed because hospitals are classified as essential facilities. It should be noted that fragility curves for C2L are used in the following evaluation of the seismic alternatives for URML-type structure, as specific fragility curves are not available in HAZUS.

11.1. Intensity measure

Response spectra, used as intensity measure (I), were generated for each of the six hospitals using the information obtained from USGS (2002). The variation of the spectral accelerations over the different hospital locations appears to be insignificant, as the structures are located close to each other. Four hazard levels are considered for generation of the loss–hazard curves, taking into account a range of levels of earthquakes in the region. These levels include earthquakes with 2%, 5% 10% and 20% probability of exceedance P in 50 years. Note that these probability levels are assigned based on a 50 year time span, and

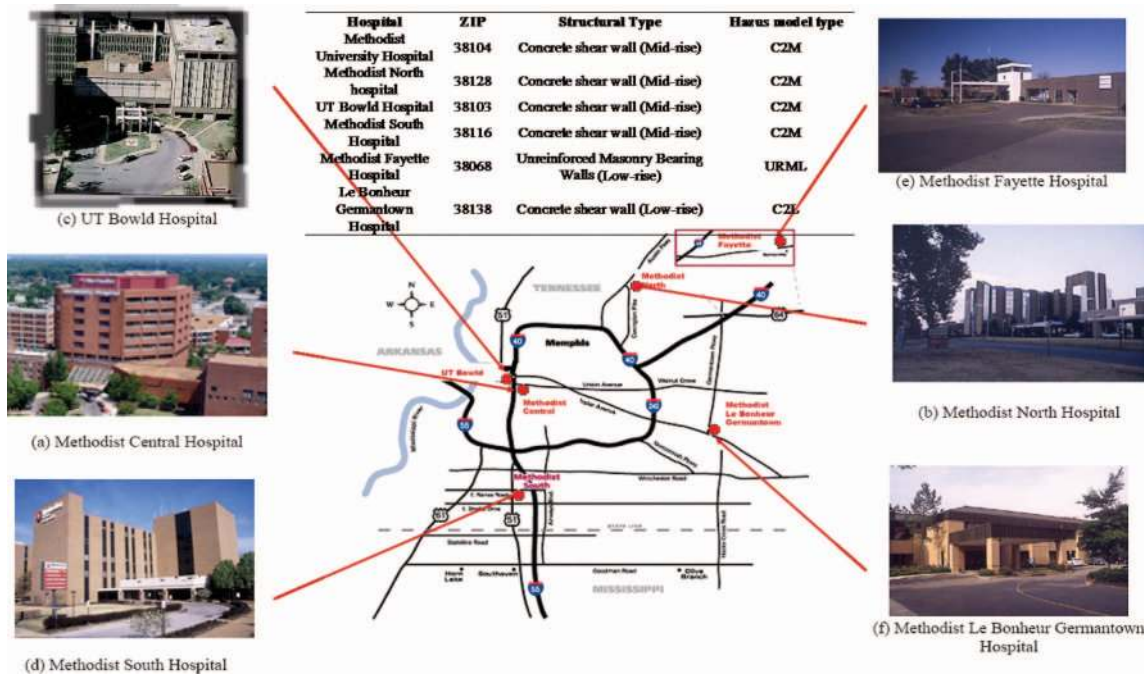

Figure 10. Hospital network definition.

Table 1. Building description.

Hospital	Location	Structural type	HAZUS model type
Methodist University Hospital	35.1394 lat.–89.9992 long.	Concrete shear wall (Mid-rise)	C2M
Methodist North Hospital	35.2222 lat.–89.9252 long.	Concrete shear wall (Mid-rise)	C2M
UT Bowld Hospital	35.1511 lat.–90.0351 long.	Concrete shear wall (Mid-rise)	C2M
Methodist South Hospital	35.0380 lat.–90.0071 long.	Concrete shear wall (Mid-rise)	C2M
Methodist Fayette Hospital	35.0380 lat.–90.0071 long.	Unreinforced masonry bearing walls (Low rise)	URML
Le Bonheur Germantown Hospital	35.0912 lat.–89.7983 long.	Concrete shear wall (Low-rise)	C2L

should be modified when a different time span T_{LC} is used, as follows:

$$P_{T_{\mathrm{LC}}} = 1 - (1 - P_{50})^{\frac{T_{\mathrm{LC}}}{50}}, \tag{23}$$

where $P_{T_{\mathrm{LC}}}$ is the probability of exceedance in a period T_{LC} (in years) for a particular intensity i^* of the earthquake and P_{50} is the probability of exceedance in 50 years for the same earthquake level. Therefore, the probability $P(I_{T_{\mathrm{LC}}} > i^*)$ that an earthquake of a given intensity occurs in a given control period T_{LC} can be adjusted according to Equation (23), and substituted to evaluate the resilience in Equations (2) and (3).

The control period of the system T_{LC} is assumed to be 30 years and a discount rate r of 6% is assumed. The control time for the decision analysis is usually based on the decision maker's interest in evaluating the retrofit alternatives. Although a 50 year control period could be chosen for evaluating the hospital systems, which may be consistent with the period used for the calculation of the earthquake hazards (e.g. as in 2% probability of exceedance in 50 years), a decision maker in charge with financing the retrofit could be interested in a shorter period that is more in line with the lifespan of a new construction. Generally, seismic losses associated with seismic vulnerable structures increase if longer control periods are considered. For example, retrofit can hardly be justified for a 1 year period because the probability of encountering a large earthquake within this period is very low, whereas the probability increases appreciably for a 50 year period, so the retrofit becomes more cost-effective in reducing losses. A decision maker siding with the user community could therefore be interested in a longer T_{LC}. In this example, a control period of 30 years is assumed

for T_{LC} as the baseline value, in line with the lifespan of the structure as mentioned above.

11.2. Performance levels

As indicated previously, four alternative actions related to retrofit are considered for each structural type: (1) no action, (2) rehabilitation to life safety level, (3) retrofit to the immediate occupancy level and (4) construction of a new building. The retrofit levels are, as defined in FEMA 276 (1999), the target performance expected for earthquake rehabilitation. The cost of seismic retrofit for building systems depends on numerous factors, such as building type, earthquake hazard level, desired performance level, occupancy or usage type. These costs generally increase as the target performance level becomes higher (e.g. rehabilitation to immediate occupancy level would obviously require more initial costs for retrofit than the retrofit to life safety level). On the contrary, with higher performance levels, less seismic losses are expected. The initial retrofit costs for the options considered here are obtained from FEMA 227 (1992) and FEMA 156 (1995), which provide typical costs for rehabilitation of existing structures, taking into account the above-mentioned factors.

11.3. Evaluation of building response

The maximum building response of these hospitals, which is used in the structural evaluation, is obtained from the intersection of the demand spectrum and the building capacity curve, which is determined from a nonlinear static (pushover) analysis (Reinhorn *et al.* 2001, FEMA 2005). The maximum building response is used in conjunction with the fragility curves to obtain the damage probability distributions (probability of being in or exceeding various damage states).

11.4. Fragility curves of hospital building types

Damage fragility curves are generated for both structural and non-structural damage, using HAZUS assessment data. The non-structural damage fragility curves consist of acceleration-sensitive components and drift sensitive components (FEMA 2005). In this way the structural, the non-structural acceleration sensitive and the drift-sensitive damage can be assessed separately using their respective fragility curves.

In this example, both structural and non-structural damage fragility curves for C2L-, C2M- and URML-type structures for different code levels are generated. Then, the multi-dimensional fragility curves are obtained by combining both structural and non-structural fragility curves, following the procedure described by Equation (3) (Cimellaro *et al.* 2006b). Figure 11 shows the multi-dimensional fragility curves for a C2M-type structure, related to the four different retrofit options and four different damage states. The hazard level is shown along the x-axis as a function of the return period that takes to account the uncertainties in estimating the ground motion intensity at the site, which has been considered as a random variable, by performing a probabilistic seismic hazard analysis.

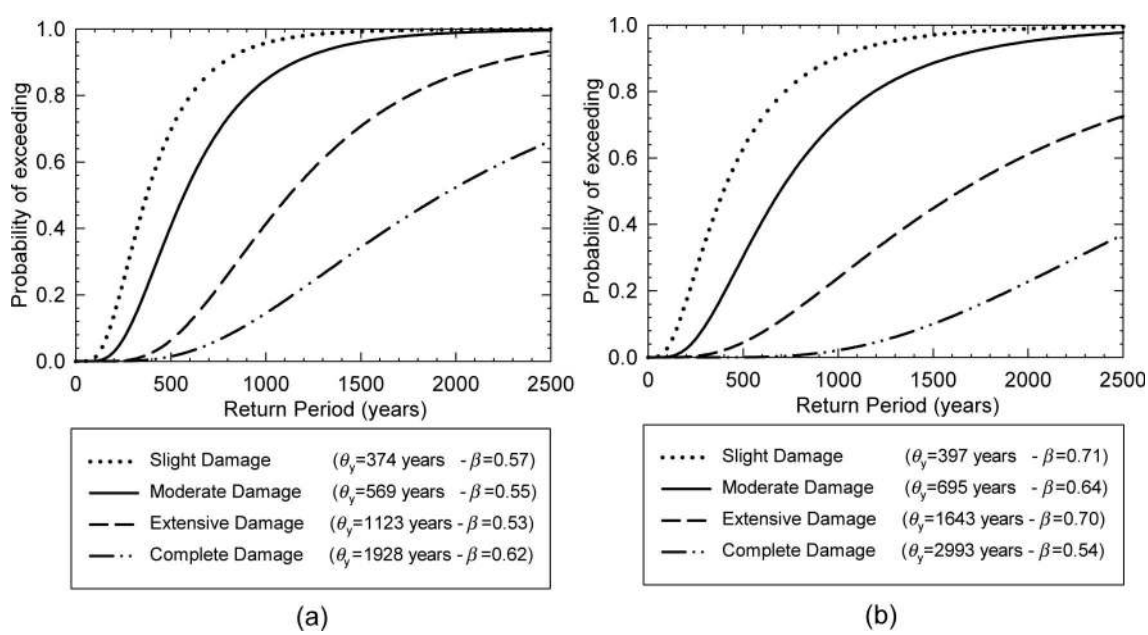

Figure 11. Multi-dimensional fragility curves for C2M structure: (a) no action and (b) rehabilitation life safety.

As shown, different action strategies lead to a move of the fragility curves to the right, indicating reduction of the probability of failure for a specific seismic hazard.

Figure 12 shows the structural performance (damage) probability distributions for C2M-type structures for different retrofit strategies for a control period of 50 years. Figure 13 shows the overall distributions for the C2M structures within a 30 year period, compared with a 50 year period. As expected, the probability of having no damage increases with the reduced control period. More details can be found in Cimellaro *et al.* (2006a).

11.5. Seismic losses in the hospital network

Among the large number of seismic losses described in the previous sections, several attributes that are typically considered to be crucial for hospital systems are selected for this study, and are listed in Table 2, along with a brief explanation of each parameter. This list is valid for this case study, and can be different according to the decision maker's choice. For example, loss of income is excluded because it is relatively less important in the calculation of monetary loss for the (hospital) system ($<5\%$ of the total monetary loss). In this case, it is assumed that the decision is taken by a public policy maker, who might be less concerned about the hospital's income when compared to a hospital administrator. It is important to mention that losses in undamaged sectors of the hospital due to business interruption are not considered in this example.

Using the performance (damage) probability distributions listed in the previous section, various seismic losses associated with the system are estimated. Table 3 shows the deterministic relationship between various damage states and the corresponding normalised seismic losses that are estimated from the fragility curves of the system for a C2M-type structure. Losses are estimated for the four earthquake levels, and loss hazard curves are generated in order to calculate the overall expected losses (not shown). Also, in Table 3, distinction is made between the number of death and injuries.

As described in Table 2, losses used in this case study should take into account the fact that loss of function in a hospital may result in additional loss of life. Using the conversion factor of $C_F = \$100{,}000$/day to recover/929.03 m^2, the normalised losses in Table 3 are determined. The expected equivalent earthquake losses for each rehabilitation scheme are shown in the third column of Table 4, which are obtained considering the probability of each level of the earthquake, along with the initial rehabilitation costs, followed by the total expected losses considering an observation period T_{LC} of 30 years.

11.6. Seismic resilience

The expected equivalent earthquake losses for each rehabilitation scheme are shown in the third column of Table 4, which are obtained considering the probability for each level of earthquake, along with the initial rehabilitation costs, followed by the total expected losses considering an observation period T_{LC} of 30 years.

If uncertainties in the seismic input are considered by using four different hazard levels, then resilience can be evaluated using Equation (3) for different

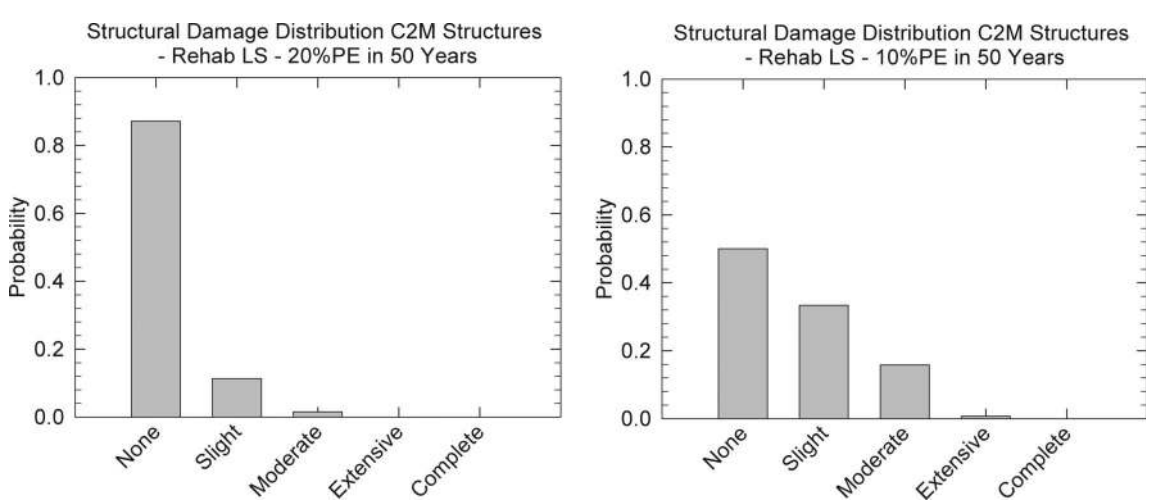

Figure 12. Structural performance (damage) distribution for rehabilitation to life safety for C2M structures: (a) 20% probability of exceedance (PE) in 50 yrs and (b) 10% PE in 50 years ($T_{LC} = 50$ years).

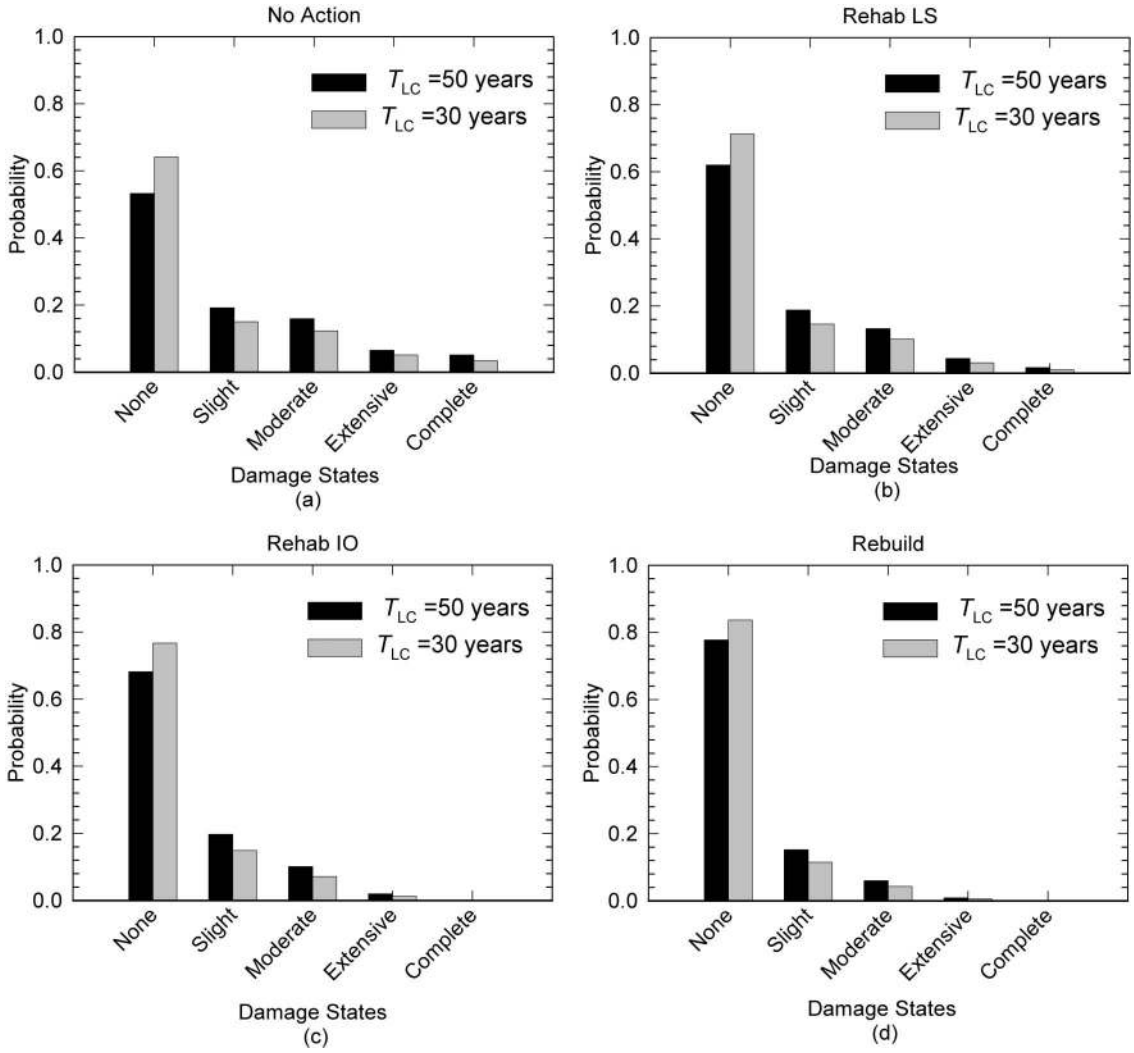

Figure 13. Structural performance (damage) distribution for different rehabilitation strategies.

Table 2. Losses considered in this case study.

Category	Loss	Description
Structural losses (L_S)	Initial cost	Cost of seismic rehabilitation or constructing a new building to improve structural performance.
	Structural repair cost	Cost for repairing damage to structural components such as beams, columns, joints, etc.
Non-structural losses (LNS)		
Direct economic losses ($L_{NS,DE}$)	Non-structural Repair costs	Cost for repairing damage to non-structural components such as architectural, electrical and mechanical items.
	Loss of building contents	Cost equivalent to the loss of building contents such as furniture, equipment (not connected to the structure), computers, etc.
Indirect economic losses ($L_{NS,IE}$)	Relocation expenses	Disruption cost and rental cost for using temporary space in case the building must be shut down for repair.
Indirect casualties losses ($L_{NS,IC}$)	Loss of functionality	Loss of function for a hospital may result in additional human life losses due to lack of medial activities and capability.
Direct casualties losses ($L_{NS,DC}$)	Death	Number of deaths.
	Injury	Number of seriously injured.

Table 3. Normalised losses ratios for different damage states of C2M buildings (Park *et al.* 2004, FEMA 2005).

(1)	(2)	Slight (3)	Moderate (4)	Extensive (5)	Complete (6)	Complete ($/m^2) (7)
L_S	Structural normalised cost	0.0176	0.1	0.5	1.0	1.58
$L_{NS,DE}$	Drift sensitive non-structural cost	0.0190	0.1	0.5	1.0	3.90
	Acceleration sensitive non-structural cost	0.0194	0.1	0.3	1.0	5.76
	Contents loss	0.0200	0.1	0.5	1.0	5.62
$L_{NS,DC}$	Death	0.000000	0.000000	0.000015	0.125000	
	Injury	0.000000	0.000300	0.001005	0.225000	
	Recovery time (days)	2	68	270	360	

Table 4. Costs, recovery time and resilience for rehabilitation strategies.

Rehabilitation alternatives (1)	Rehabilitation costs $ million* (2)	Expected earthquake loss $ million* (3)	Total costs ($ million) (4)	Recovery time T_{RE} (days) (5)	Resilience Res (%) (6)
No action	0.0 (0%)	32.3 (37%)	119.7	65	65.0
Life safety (LS)	32.8 (38%)	18.8 (22%)	138.9	38	87.1
Immediate occupancy (IO)	66.4 (76%)	9.54 (11%)	163.2	10	96.8
Rebuild	92.3 (106%)	5.82 (7%)	185.4	6	98.7

*Percentage of initial investments.

rehabilitation strategies and compared, as shown in Figure 14.

The initial costs of rehabilitation for different rehabilitation strategies, the expected equivalent earthquake loss and the total costs (including the initial costs of the entire system that is estimated equal to $87.3 million) are all reported in Table 4.

The recovery time and resilience values are also summarised in Table 4. For this case study, it is shown that the rebuild option has the largest value of seismic resilience of 98.7% when compared with the other three strategies, but it is also the most expensive solution ($92.3 million). However, if no action is taken, the seismic resilience is still reasonably high (65.0%). As shown in this case study, initial investments and resilience are not linearly related. When the functionality $Q(t)$ is very high, improving it by a small amount requires investing a very large amount compared with the case when the function $Q(t)$ of the system is low. Although this is an obviously expected engineering outcome, the procedure presented here provides a quantification that may be used by decision makers.

12. Concluding remarks

This paper presents a comprehensive conceptual model of quantification of resilience, which includes both loss estimation models and recovery models and can be applied to complex systems of structures and infrastructure networks. The proposed model is a framework that becomes more complex when comprehensive loss estimation or recovery models (e.g. metamodels for the case of health-care facilities) are used. Indeed, current research trends lead toward the definition of more complex recovery models that are able to describe the process over time and the spatial definition of recovery. In fact, although many studies can be found on loss estimation models, little research has been found on recovery models because the complexity of each model is specific to the problem at hand. An integrated loss and recovery organisational efficiency model is presented for critical-care facilities.

Many assumptions and interpretations have to be made in the quantification of the aggregated seismic resilience. However, the final goal is to integrate the information from these different fields (engineering, economics, operations, etc.) into a unique function, leading to results that are unbiased by uninformed intuition or preconceived notions of risk. The formulation presented herein includes the physical structural aspects and the organisational efficiency using simplistic probability models, aggregated in a single resilience measure, while preserving information about major

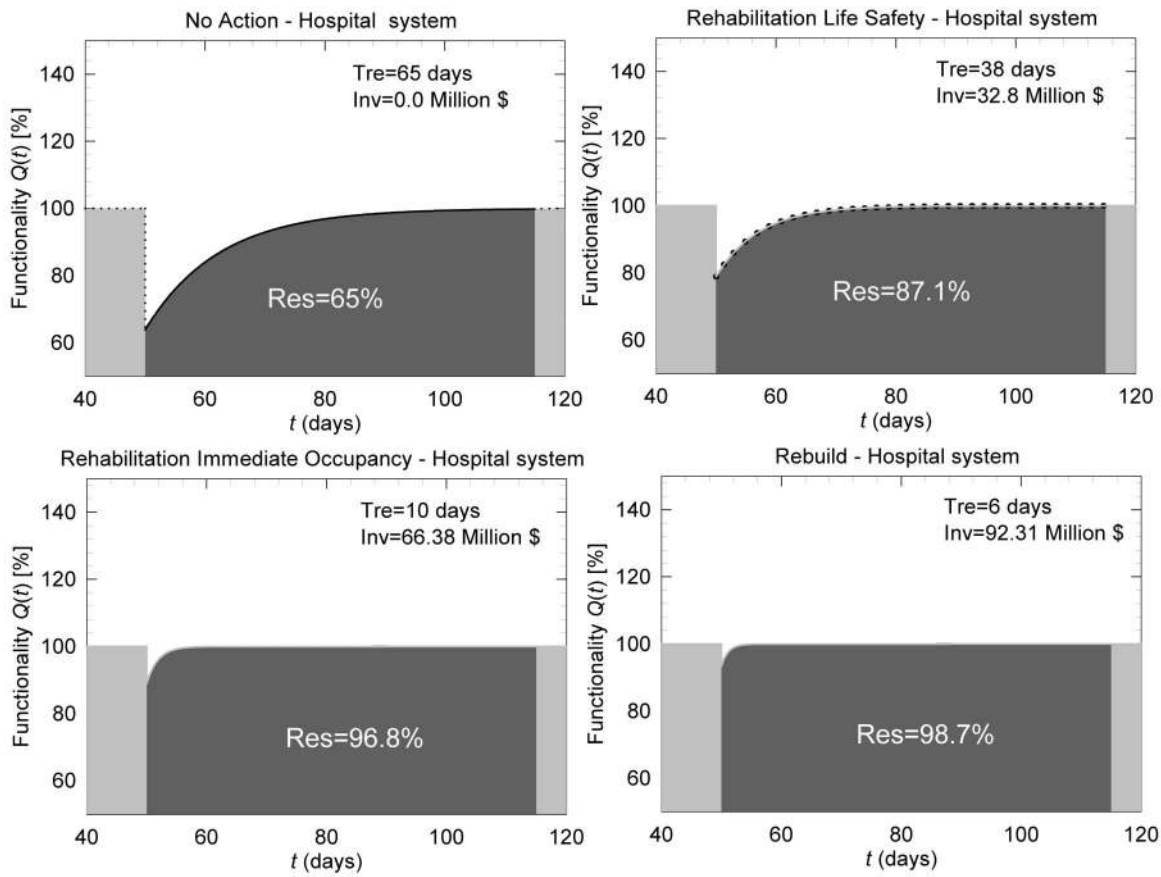

Figure 14. Functionality curves: (a) no action, (b) life safety rehabilitation, (c) immediate occupancy rehabilitation and (d) rebuild for entire hospital system.

contributors (parameters), such as retrofit techniques and emergency demands.

The framework model proposed has been applied to a network of six hospitals located in Memphis, Tennessee, USA using a simple loss estimation and recovery model, while more complex recovery models for hospitals (metamodels) are presented. Such recovery models, currently under development, can be a combination of one or more of the simplified recovery models presented herein. However, it is important to note that the assumptions made are only representative for the case study. For other problems, users can focus on those assumptions that are mostly affecting the problem at hand, while using the case study as guidance.

Acknowledgements

This research was supported in part by the Earthquake Engineering Research Centers Program of the National Science Foundation (NSF) under Award Number EEC-9701471 to MCEER and by the State of New York (NYS). Any opinions, findings and conclusions or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of the sponsors.

References

Alexander, D., 1996. The health effects of earthquakes in the mid-1990s. *Disasters*, 30 (3), 231–247.

Alesch, D.J. and Petak, W.J., 2004. Seismic retrofit of California hospitals: implementing regulatory policy in a complex and dynamic context. *ASCE Natural Hazards Review*, 5 (2), 89–96.

Blockley, D., 1999. Risk based structural safety methods in context. *Structural Safety*, 21, 335–348.

Bruneau, M. and Reinhorn, A.M., 2004. Seismic resilience of communities – conceptualization and operationalization. *In*: P. Fajfar and H. Krawinkler, eds. *Performance-based seismic design-concepts and implementations, Proceedings of international workshop on performance based seismic-design*, 28 June–1 July, Bled, Slovenia, PEER report 2004/05, University of California at Berkeley, 161–172.

Bruneau, M. and Reinhorn, A.M., 2007. Exploring the concept of seismic resilience for acute care facilities. *Earthquake Spectra*, 28 (1), 41–62.

Bruneau, M., Chang, S., Eguchi, R., Lee, G., O'Rourke, T., Reinhorn, A.M., Shinozuka, M., Tierney, K., Wallace, W., and Winterfelt, D.V., 2003. A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra*, 19 (4), 733–752.

Chang, S., 2000. Disasters and transport systems: loss, recovery, and competition at the Port of Kobe after 1995 earthquake. *Journal of Transport Geography*, 8 (1), 53–65.

Chang, S. and Shinozuka, M., 2004. Measuring improvements in the disaster resilience of communities. *Earthquake Spectra*, 20 (3), 739–755.

Cimellaro, G.P. and Reinhorn, A.M., 2009. Multidimensional performance limit states for evaluation of structural fragility. *Journal of Engineering Mechanics, ASCE,* in review.

Cimellaro, G.P., Reinhorn, A.M., and Bruneau, M., 2005. Seismic resilience of a health care facility. *In*: *Proceedings of annual meeting of the Asian Pacific network of Centers for Earthquake Engineering Research (ANCER)*, 10–13 November 2005, Seogwipo KAL Hotel, Jeju, Korea, paper N3-Session III.

Cimellaro, G.P., Reinhorn, A.M., and Bruneau, M., 2006a. Quantification of seismic resilience. *In*: *Proceedings of 8th national conference of earthquake engineering*, 8–22 April, San Francisco, CA, paper 1094.

Cimellaro, G.P., Reinhorn, A.M., Bruneau, M., and Rutenberg, A., 2006b. *Multidimensional fragility of structures: formulation and evaluation*. Buffalo, NY: University at Buffalo, the State University of New York, Report MCEER-06-0002.

Cimellaro, G.P., Fumo, C., Reinhorn, A.M., and Bruneau, M., 2009a. Quantification of Disaster Resilience for Health care facilities. *MCEER Technical Report*, University at Buffalo, The State University of New York, Buffalo, NY, USA.

Cimellaro, G.P., Reinhorn, A.M., and Bruneau, M., 2009b. Framework for the analytical quantification of disaster resilience of structures. *Structural Safety*, in review.

Coburn, A. and Spence, R.J.S., 2002. *Earthquake protection*. Chichester, UK: John Wiley & Sons.

Cornell, A. and Krawinkler, H., 2000. Progress and challenges in seismic performance assessment. *Peer News*, April, 3 (2).

Federal Emergency Management Agency (FEMA), 1992. *A benefit-cost model for the seismic rehabilitation of buildings*. Washington, DC: Federal Emergency Management Agency and US Army Corps of Engineers, FEMA 227.

Federal Emergency Management Agency (FEMA), 1995. *Typical costs for seismic rehabilitation of existing buildings, vol 1 – summary*. Washington, DC: Federal Emergency Management Agency and US Army Corps of Engineers, FEMA 156.

Federal Emergency Management Agency (FEMA), 1999. *Example applications of the NEHRP guidelines for the seismic rehabilitation of buildings*. Washington, DC: Federal Emergency Management Agency and US Army Corps of Engineers, FEMA 276.

Federal Emergency Management Agency (FEMA), 2005. *HAZUS-MH, version 1.1, FEMA's software program for estimating potential losses from disasters, Technical manual*. Washington, DC: Federal Emergency Management Agency and US Army Corps of Engineers. Available from: http://www.fema.gov/hazus.

Filiatrault, A., Uang, C.-M., Folz, B., Christopoulos, C., and Gatto, K., 2001. *Reconnaissance report of the February 28, 2001 Nisqually (Seattle-Olympia) earthquake*. San Diego: University of California at San Diego (UCSD), UCSD report no. SSRP- 2001/02.

Kafali, C. and Grigoriu, M., 2005. Rehabilitation decision analysis. *In*: *ICOSSAR'05, Proceedings of the 9th international conference on structural safety and reliability*, 19–23 June, Rome, Italy.

Kendra, J. and Wachtendorf, T., 2003. Elements of resilience after the World Trade Center disaster: reconstructing New York City's emergency operations centre. *Disasters*, 27 (1), 37–53.

Maxwell, R.J., 1984. Quality assessment in health. *British Medical Journal*, 288 (6428), 1470–1472.

McCarthy, K., McGee, H.M., and O'Boyle, C.A., 2000. Outpatient clinic waiting times and non-attendance as indicators of quality. *Psychology, Health and Medicine*, 5, 287.

Miles, S.B. and Chang, S.E., 2006. Modeling community recovery from earthquakes. *Earthquake Spectra*, 22 (2), 439–458.

National Research Council (NRC), 1992. *The economic consequences of a catastrophic earthquake*. Washington, DC: National Academy Press.

Okuyama, Y. and Chang, S.E.-L., 2004. *Modeling spatial and economic impacts of disasters*. Berlin: Springer-Verlag.

Park, J., Nojima, N., and Reed, D.A., 2006. Nisqually earthquake electric utility analysis. *Earthquake Spectra*, 22 (2), 491–509.

Park, J., Goodno, B., Bostrom, A., and Craig, J., 2004. Probabilistic decision analysis for seismic rehabilitation of a regional building system. *In*: *Proceedings of 13th world conference on earthquake engineering*, 1–6 August, Vancouveraer, BC, paper 2254.

Paul, J.A., George, S.K., Yi, P., and Lin, L., 2006. Transient modelling in simulation of hospital operations for emergency response. *Prehospital and Disaster Medicine*, 21 (4), 223–236.

Peek-Asa, C., Kraus, J.F., Bourque, L.B., Vimalachandra, D., Yu, J., and Abrams, J., 1998. Fatal and hospitalized injuries resulting from the 1994 Northridge earthquake. *International Journal of Epidemiology*, 27 (3), 459–465.

Reinhorn, A.M., Barron-Corverra, R., and Ayala, A.G., 2001. Spectral evaluation of seismic fragility of structures. *In*: *Proceedings of ICOSSAR 2001*, June 2001, Newport Beach, CA.

Taghavi, S. and Miranda, E., 2003. Probabilistic study of peak floor acceleration demands in linear structures. *International Conference on Applications of Statistics and Probability in Civil Engineering*, San Francisco, CA, 1565–1572.

United States Geological Survey (USGS), 2002. *National seismic hazard mapping project, version 2002*. Available from: http://eqint.cr.usgs.gov/eq/html/lookup-2002-interp.html.

Vieth, T.L. and Rhodes, K.V., 2006. The effect of crowding on access and quality in an academic ED. *American Journal of Emergency Medicine*, 24 (7), 787.

Viti, S., Cimellaro, G.P., and Reinhorn, A.M., 2006. Retrofit of a hospital through strength reduction and enhanced damping. *Smart Structures and Systems*, 2 (4), 339–355.

Whitman, R.V., Anagnos, T., Kircher, C.A., Lagorio, H.J., Lawson, R.S., and Schneider, P., 1997. Development of a national earthquake loss estimation methodology. *Earthquake Spectra*, 13 (4), 643–662.