SEISMIC RESILIENCE OF HEALTH CARE FACILITIES

G.P. Cimellaro[1] Cristina Fumo[2] A. Reinhorn[3] and M. Bruneau[3]

[1] *Postdoctoral Research Associate, Department of Civil, Structural & Environmental Engineering - University at Buffalo- (SUNY), Buffalo, NY 14260 - USA Email: cimellaro@gmail.com*

[2] *Ph.D. Candidate, Department of Civil Engineering, University of Udine. Via delle Scienze, 208 33100 – Udine – Italy*

[3] *Professor, Department of Civil, Structural & Environmental Engineering - University at Buffalo- (SUNY), Buffalo, NY 14260 - USA*

ABSTRACT :
Resilience is defined as the ability of engineering and socio-economic systems to rebound after severe disturbances, or disasters, such as earthquakes. This paper presents a comprehensive conceptual framework to quantify resilience including both technical and organizational aspects. An organizational model (metamodel) describing the response of the hospital emergency department has been implemented. The metamodel is able to estimate the hospital capacity and its dynamic response in real time and incorporate the influence of the facility's damage in structural and non-structural systems on the organizational ones. The waiting time, a measure of efficiency and capability to respond, it is used to evaluate seismic resilience of health care facilities. Its behavior is described using a double exponential function and its parameters are calibrated based on simulated data. The metamodel has been designated to cover a large range of hospital configurations and takes into account hospital resources, in terms of staff and infrastructures, operational efficiency and possible existence of an emergency plan, maximum capacity and behavior both in pre-saturated and saturated conditions.

KEYWORDS:
Damage state, functionality, hospital, metamodel, organization, resilience.

1. INTRODUCTION

Health care facilities have been recognized as strategic buildings in hazardous events and play a key role in the disaster response and recovery; however no attempt was made so far to practically relate the structural and organizational damage on the performance of hospitals. There is an extensive literature on the definition of the main parameters of seismic resilience (see Bruneau *et al.*, 2003; Bruneau and Reinhorn, 2007; Cimellaro *et al.*, 2008) for health care systems and on the definition of the general framework, however there is no information regarding the modeling and the measure of the organizational aspects of resilience. Indeed, an organizational resilience model is needed, to be able to determine the response of the community to hazardous events, and evaluate the real loss in terms of healthy population and quality of care provided. In this paper an organizational metamodel describing the response of the hospital's emergency department (ED) has been implemented. The model intends to offer a first approach to the problem and a more comprehensive evaluation of the multidimensional aspects of resilience. The metamodel is able to estimate the hospital capacity and incorporate the influence of the facility damage in structural and non-structural components on the organizational ones.

2. ORGANIZATIONAL RESILIENCE

The main purpose of this research is to relate the technical and organizational aspects of health care facilities, to obtain a measure of organizational resilience that has not been attempted so far. The goal is to relate the measure of resilience to the quality of care (QC) provided and the eventual loss of healthy population, caused by the performance of the health care facility during the disaster. Resilience is defined in this paper as a function indicating the capability to sustain a level of functionality or performance for a given building, bridge, lifeline networks, or community, over a period T_{LC} defined as the control time that is usually decided by owners, or society (usually is the life cycle, life span of the system etc.). This quantity is defined graphically as the normalized shaded area (Figure 1) underneath the functionality function Q(t) of a system and is defined analytically as follows:

$$R = \int_{t_{OE}}^{t_{OE}+T_{LC}} Q(t)/T_{LC}\, dt \tag{2.1}$$

where the functionality Q(t) ranges from 0 to 100%. 100% mean 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). Then within a period called recovery period T_{RE}, the system will be able to return to the same level of functionality before the extreme event.

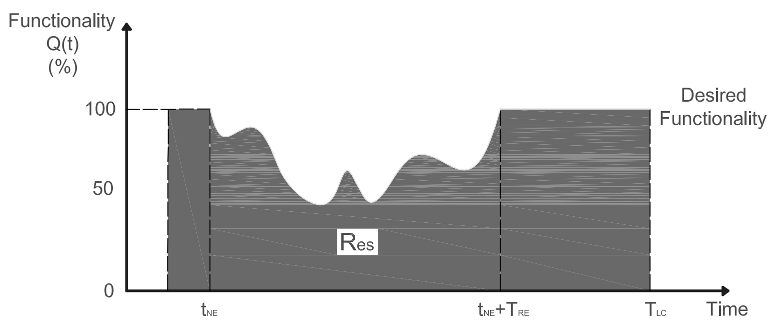


Figure 1 Schematic representation of seismic resilience

The system diagram in Figure 2 identifies the key steps of the framework to quantify resilience. The left part of the diagram mainly describes the steps to quantify *technical* aspects of resilience while the right side describes the *organizational* aspects to quantify resilience. The penalty factors *PF* that appear in the diagram describe the interaction between the technical and the organizational aspects and their evaluation is discussed in one of the following paragraph.

2.1. Functionality of a hospital facility

In order to define resilience it is necessary to define first the functionality Q of the hospital facility. Functionality is defined as the combination of two components:

1. Qualitative functionality Q_{QS} related to the quality of service (QS);
2. Quantitative functionality Q_{LS} related to the losses in healthy population;

Qualitative functionality is related to the QS, as indicated by a relevant literature review reported in various references (Maxwell, 1984; Mc Carthy et al. 2000; Vieth and Rhodes, 2006). Therefore, if a measure of QS is found then it is possible to measure the functionality Q of the health care facility. As it will be discussed in the following paragraph 2.2, the QS can be related to the waiting time (*WT*) spent by people in the emergency room while requiring care. The *WT* is the main parameter to valuate the response of the hospital during normal time and the hazardous event. Analytically, qualitative functionality has been defined as:

$$Q_{QS}(t) = (1-\alpha) Q_{QS,1}(t) + \alpha Q_{QS,2}(t) \tag{2.2}$$

that is a linear combination of two functions, $Q_{QS,1}$(t)and $Q_{QS,2}$(t), expressed in Eqn. (2.3) respectively, while α is a weight factor that combine the two functions describing the behavior in non saturated and saturated conditions.

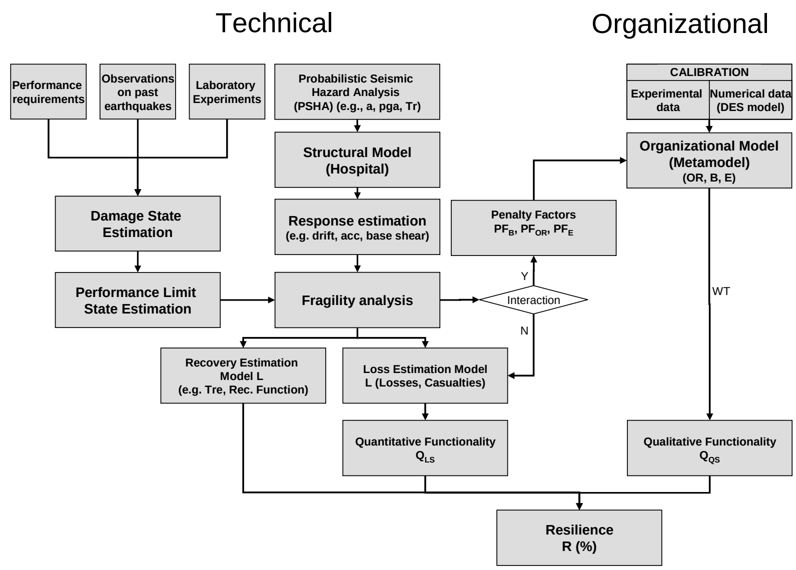


Figure 2 Resilience framework (MCEER approach)

In particular, in non saturated condition ($\lambda \leq \lambda_U$), and saturated conditions ($\lambda \geq \lambda_U$), the QS is described by the function $Q_{QS,1}$(t) and $Q_{QS,2}$(t) respectively

$$Q_{QS,1}(t) = \frac{\max\left(\left(WT_{crit} - WT(t)\right),\ 0\right)}{WT_{crit}} \quad if \quad \lambda \leq \lambda_u \qquad Q_{QS,2}(t) = \frac{WT_{crit}}{\max\left(WT_{crit}, WT(t)\right)} \quad \lambda > \lambda_u \qquad (2.3)$$

The qualitative functionality expressed in Eqn. (2.2) is showed in Figure 3a, while the weighting factor α ranging from 0 to 1. Following the definition of qualitative functionality given in Eqn. (2.2), the hospital is fully functional when is able to absorb with a minimum delay all the patients requiring care.
However, QS is a good indicator of functionality only in non saturated conditions. When the hospital operates in saturated condition (when the maximum capacity of the hospital is reached) it is not able to guarantee the normal level of QS, because the main goal now is to provide treatment to the most number of patients. Therefore, in this case the number of patients treated N_{TR} is a good indicator of functionality Q. The quantitative functionality Q_{LS}(t) is then defined as a function of the losses L(t), which are defined as the total number of patients not treated N_{NTR} versus the total number of patients requiring treatment N_{tot}. In this case the functionality is defined as follows

$$Q_{LS}(t) = 1 - L(t) = 1 - \frac{N_{NTR}(t)}{N_{tot}(t)} = \frac{N_{TR}(t)}{N_{tot}(t)} \qquad (2.4)$$

where the total number of patients requiring care N_{tot} and the total number of patients that do not receive treatment N_{NTR} are given by the following formulas

$$N_{tot}(t) = \int_{t_0}^{t_0+t} \lambda(\tau)\cdot d\tau \qquad N_{NTR}(t) = 1 - N_{TR}(t) = 1 - \int_{t_0}^{t_0+t} \min\left(\lambda(\tau), \lambda_u\right)\cdot d\tau \qquad (2.5)$$

The trend of the total number of patients going to the hospital right after an earthquake and the number of patients treated is shown in Figure 3b. According to this definition, the hospital is fully functional when is able to treat all the patients going to the hospital. If the number of patients treated is smaller than the number of patients requiring treatment, then the quantitative functionality Q_{LS} decreases as shown in Figure 3c. Finally, the total functionality Q(t) of the hospital is shown in Figure 3d and it is given by

$$Q(t) = Q_{QS}(t) \cdot Q_{LS}(t) \tag{2.6}$$

The global functionality Q of Eqn. (2.6) is shown in Figure 3d. It is important to mention that Q_{QS} requires the estimation of WT and its estimation is given in the following paragraph.

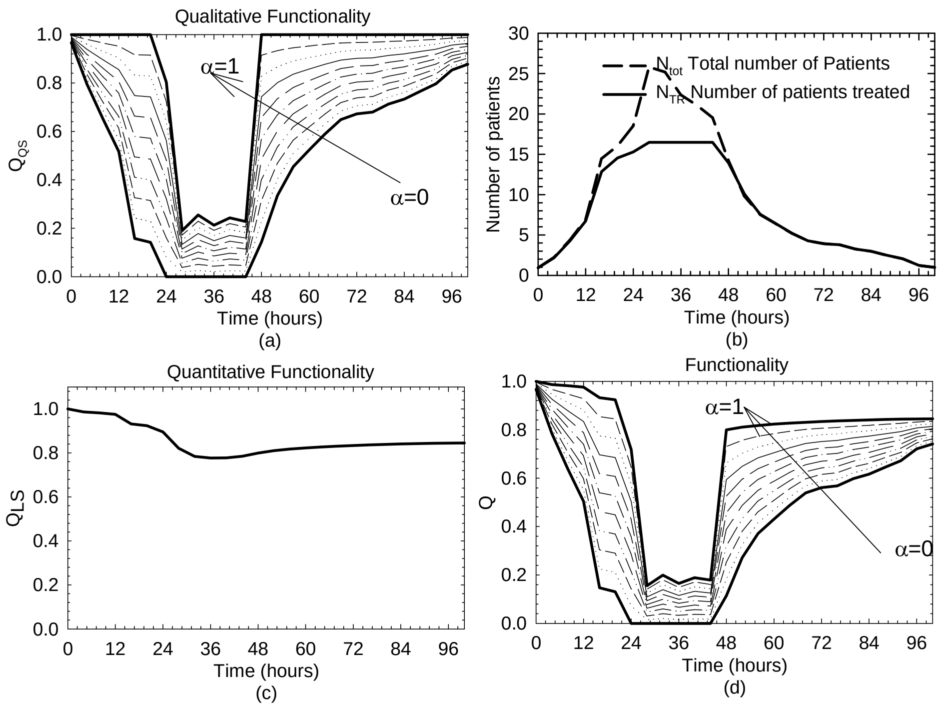


Figure 3 Functionality of health care facility

2.2. Waiting time as a measure of the quality of service

The first issue to solve when approaching the problem of modeling of a health care system is defining the main parameter of response that can be used to measure the functionality of a hospital. A well acknowledged study (Maxwell, 1984) has demonstrated that waiting time (*WT*) in an ED may be used as a key parameter in the quantification of the QS in health care settings; therefore it can be used as a measure of the accessibility, efficiency, and relevance of the outpatient service. *WT* is defined as the time elapsed between the received request of care by the hospital and the provision of the care to the patient. This parameter is related to the hospital resources (e.g. number of beds, B), in particular to those of the ED, such as stuff on duty, number of labs and operating rooms (OR) grade of utilization of the OR, but also to the degree of crowding of the ED.
Many models are available in literature (see Cimellaro *et al.*, 2008) to measure the WT of health care facilities. However, in this research we focus on *discrete events simulation models* (DES) and *metamodels* that will be described in detail in the following paragraph. Further details can be found in Cimellaro *et al*. (2008).

2.3. Discrete event simulation model vs. Metamodel

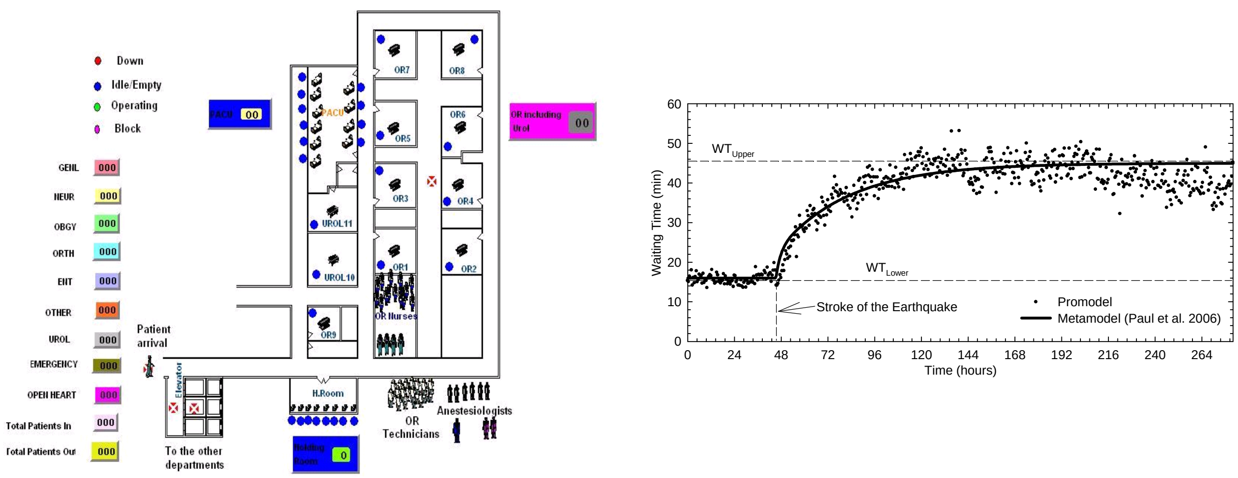
Health care systems are inherently complicated, in terms of details, dynamic and organizational aspects, because of the existence of multiple variables, which potentially can produce an enormous number of connections and effects. The presence of relationships not obvious over time, the difficulties (or impossibility) to quantify some variables (e.g. the quality and value of treatment, the WT and patient expectation on emergency admission), are only few factors that affect the error in the valuation of the actual response. Furthermore, in a disaster, the emergency adds more complexity to the health care system. The increase of the patient flow, the consequent crowding of the ED, the chaos and disorganization that may result from the resuscitation of a patient in extremis are the most stressful conditions in a hospital. Several modeling methods are available in literature to represent these complex hospital operations. Among all, DES models are valuable tools for modeling the dynamic operation of a complex system, and in particular the emergency nature of a disaster can be easily incorporated in discrete event simulation, for different types of hospitals (Lowery, 1993). A DES model usually deals with *p* deterministic input parameters, defined over a feasible region ψ, and *q* stochastic output variables such as:

$$\psi = \left(\psi_1, \psi_2, \ldots\ldots, \psi_p\right) \xrightarrow{Y=Y(\psi)} Y = \left(Y_1, Y_2, \ldots\ldots, Y_q\right) \tag{2.7}$$

In the single response optimization it is necessary to define a real function of *Y*, for example *C*=*C*(*Y*), that combines all the *q* output variables into a single stochastic one. The goal is to find out which set of ψ variables optimizes the simulation response function $F(\psi)$, such as:

$$\overline{\psi} = \left(\overline{\psi}_1, \overline{\psi}_2, \ldots\ldots\ldots, \overline{\psi}_q\right) \ : \ F\left(\overline{\psi}\right) = E\left[C\left(Y\left(\overline{\psi}\right)\right)\right] \tag{2.8}$$

The problem is that $F(\psi)$ cannot be observed directly, but rather must be estimated. This may require multiple simulations run replications or long simulation runs. The stochastic nature of the output from the simulation run complicates the optimization problem.



(a) (b)

Figure 4 (a) Discrete event simulation model of the Mercy hospital in Buffalo, NY; (b) Metamodel (Paul et al. 2006)

In Figure 4a is shown an example of a DES model of the ED of the Mercy Hospital located in Buffalo, NY, that has been build using visual simulator software developed by Promodel Corporation, (Promodel v 4.2, 1999). However, although DES models are valuable tools for hospital modeling, they are time-consuming because they require multiple simulation runs for the results to be acceptable statistically due to the random nature of simulation experiments. Furthermore, it is not possible to build DES models for all the available hospitals in the disaster area, which may vary in size after the event occurs. On the other hand, metamodels are easier to manage and provides more insights than DES models. A metamodel is simple set of equations that does not require a long execution time as in the case of DES models, therefore it becomes a good candidate for modeling operations for any general hospital in disaster condition. The patient WT is the output variable of the simulation with the metamodel that is a double exponential function defined as follows:

$$WT(t) = \left[WT(0) + \int_0^{t'} \frac{1}{\tau_1 \tau_2} \left\{ (\tau_1 - \tau_2) \exp \left\{ \frac{1}{\tau_1 \tau_2} \left[A\tau_1\tau_2 + B\lambda(t)\tau_1\tau_2 - \int_0^{t'} \left(-\tau_1 e^{C+D\lambda(t)} - \tau_2 + \tau_2 e^{C+D\lambda(t)} \right) dt + C\lambda(t)\tau_1\tau_2 + D\tau_1\tau_2 \right] + \right.\right.\right.$$

$$+\tau_2 \exp\left\{\frac{1}{\tau_1\tau_2}\left[A\tau_1\tau_2 + B\lambda(t)\tau_1\tau_2 - \int_0^{t'}\left(-\tau_1 e^{C+D\lambda(t)} - \tau_2 + \tau_2 e^{C+D\lambda(t)}\right)dt\right]\right\}dt\Bigg]\exp\left[\int_0^{t'}\left(-\frac{e^{C+D\lambda(t)}}{\tau_2} - \frac{1}{\tau_1} + \frac{e^{C+D\lambda(t)}}{\tau_1}\right)dt\right]; \quad \text{if } \lambda < \lambda_{\mathrm{U}} \quad (2.9)$$

$$WT(t) = WT(t, \lambda = \lambda_U) + \left(\frac{\lambda(t) - \lambda_U}{\lambda_U}\right)_i \cdot \left(t - t_{\lambda_U}\right); \quad \text{if } \lambda \geq \lambda_{\mathrm{U}}$$

where τ_1 and τ_1 are time constants that describe the time the system takes to reach the steady state condition. They are dependent on the arrival rate and they are determined with the least square method of estimation (Cimellaro *et al*. 2008). *A*, *B*, *C* and *D* are constants that depend on the particular hospital configuration. The metamodel needs to be calibrated, and the first problem to handle when dealing with disaster is the lack of data. This deficiency (Stratton *et al.*, 1996) is related to the difficulties in collecting data during a disaster, because the emergency activity is the first aim, and the registration of the patient is, of course, not done with the usual procedure. Because of the above reasons, all parameters of the metamodel are regressed using outputs from DES model. The advantage of the double exponential function with respect to the single exponential function is in the calibration of the constants that are obtained without the need for simulation runs for any patient arrival rate. Simulations are only necessary for the lower bound (base case) and the upper bound (critical case) of the arrival rate (Paul *et al.*, 2006). An example of the shape of this function is given in Figure 4b, where the dots are the patient waiting time obtained from simulations with DES model.

3. INTERACTION OF TECHNICAL AND ORGANIZATIONAL RESILIENCE

Structural and non–structural damage cause reduction of functionality of the hospital at the organizational level. The metamodel is able to take into account the effect of damage on the organizational model by incorporating penalty factors. The penalty factors PF_i for each structural or non structural component are given by the linear combination of the conditional probability *P* of having a certain level of damage. Four levels of damage are traditionally considered: P_1 slight, P_2 moderate, P_3 extensive and P_4 complete. The total penalty factor affecting each component analyzed is given

$$PF_i = 0.25 \cdot (P_1 - P_2) + 0.50 \cdot (P_2 - P_3) + 0.75 \cdot (P_3 - P_4) + P_4 \leq 1 \quad (2.10)$$

The total penalty factor PF_{tot} affecting all the organizational parameters of the hospital is given by linear combination of the individual penalty factors taking into account the cost of each component on the overall cost of the building

$$PF_{tot} = w_1 PF_{str} + \sum_{i=2}^{n} \frac{(1 - w_1)}{n} PF_i \leq 1 \quad (2.11)$$

where w_1 is the weighting factor of the structural component of the building; PF_{str} is the penalty factor of the structural component of the hospital; PF_i is the penalty factors of the non structural components considered and n is the number of non structural components.

4. CASE STUDY: STATISTICAL HOSPITAL MODEL

The example showed is a statistical hospital model, representative of a typical configuration of a Californian hospital (Figure 5). The parameters of the metamodel are calibrated from the statistical analysis of data obtained on a set of simulation runs performed by Yi (2005) and Paul *et al*. (2006), using a DES model during the post earthquake event. Regression equations are obtained for both pre-earthquake and post-earthquake waiting times using average daily patient arrival rates calculated from national statistics. For the case of patient inflow to an ED during an earthquake the only data available are those collected during the Northridge Earthquake that are the one that will be used in this example. The sensitivity of resilience to the main parameters that characterize the organizational metamodel is investigated. In Figure 6a is keep constant the efficiency (E=900) and the number of operating room (OR=10), while the number of beds is increased. Plot shows that the number of beds does not have a relevant effect on improvement of resilience for this type of configuration. Increasing the efficiency E for medium size hospitals does not have a relevant impact either (Figure 6b). On the other hand, Figure 6c shows that for a medium size hospital (B=300) the best way to improve the organizational resilience of the hospital is to increase the number of operating rooms OR. The weighting factor α used for the qualitative functionality in Eqn. (2.2) is equal to 0.8.

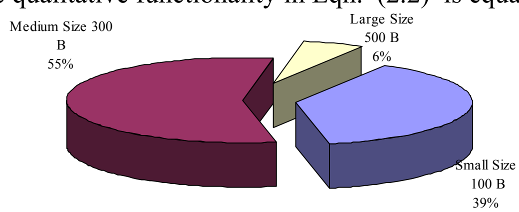


Figure 5 Composition of California hospitals

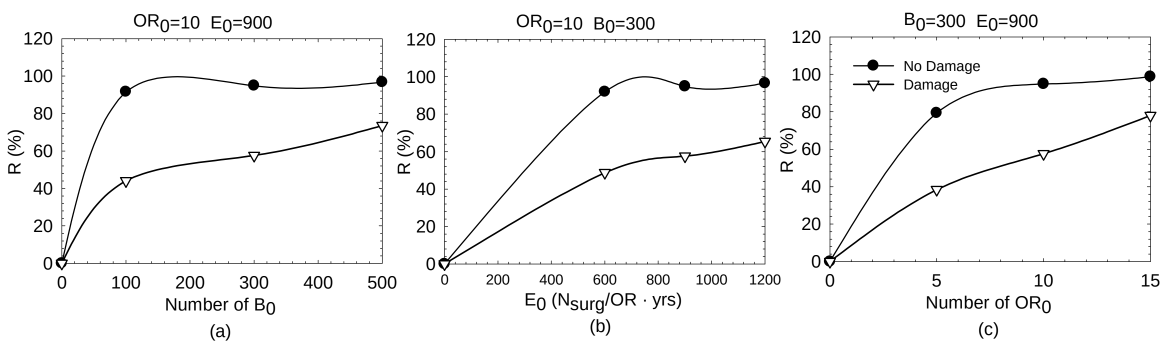


Figure 6 Sensitivity to different parameters of the metamodel

During a disaster, a hospital can apply the so called 'surge in place response'. It can increase its capability (availability of beds and staff) to new patients with a premature discharge of those inpatients whose conditions are considered stable, but who would remain hospitalized in normal operational conditions. It also can adapt the existing surge capacity, organizing temporary external shelters. The discharge function is not an exact science, and there is no mathematical formulation however usually 10 – 20 % of operating bed capacity can be mobilized within a few hours and the availability of OR can increase of 20 – 30 %.

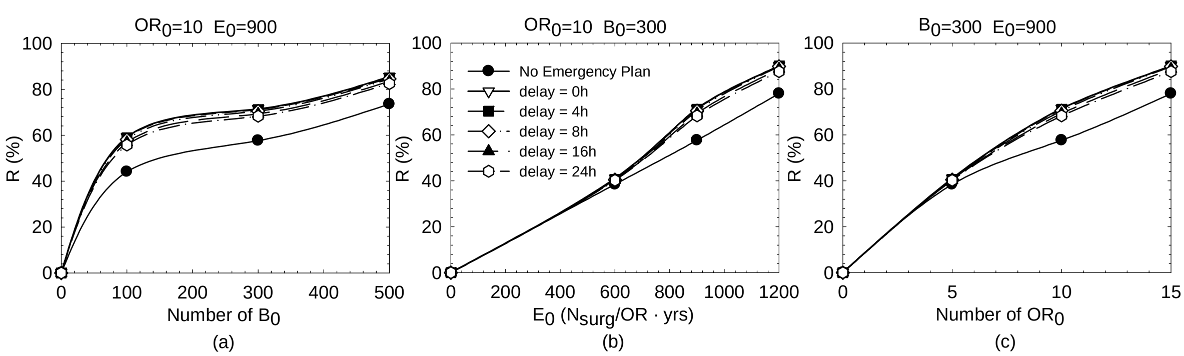


Figure 7 Sensitivity of the Emergency Plan

In Figure 7 the effect of the application of the emergency plan on the values of resilience has been investigated. It is assumed that the emergency plan increases the number of beds of 10 % and the surgery capacity (number of OR) of 30%. Resilience is plot as function of the delay in the time of application of the emergency plan, which acts as a sudden increase in the values of the organizational parameters (in this case number of beds and number of operating room) with a certain delay from the stroke of the earthquake (0, 4, 8 or 16 and 24 hours). The emergency plan has a benefic effect only in the case of medium and large size hospitals, with a medium high surge capacity (10 – 15 OR) as shown in Figure 7c.

5. CONCLUDING REMARKS

When a resilient organization is developed, such as a hospital, it is not only "hardened" to withstand disruptions from multiple hazards, but it is also more efficient on day-to-day functions. When an extreme event affects an entire region, resilient hospitals will bounce back to functionality rapidly which could improve response of entire community. This paper presents a comprehensive conceptual framework to quantify resilience including both technical and organizational aspects. A double exponential model with parameters estimated from regression analysis is used as a substitute of a complex discrete model to describe the transient operations in the hospital that are globally represented by the patient "waiting time". The effect of facility damage, as well as the resources influencing functionality, is also included in the organizational model to allow the evaluation of the hospital resilience. The framework has been applied to a typical hospital facility located in California.

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