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Performance-based metamodel for healthcare facilities

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SUMMARY

This paper introduces an organizational model describing the response of the Hospital Emergency Department (ED). The metamodel is able to estimate the hospital capacity and the dynamic response in real time and to incorporate the influence of the damage of structural and non-structural components on the organizational ones. The waiting time is the main parameter of response and it is used to evaluate the disaster resilience index of healthcare facilities. Its behaviour is described using a double exponential function and its parameters are calibrated based on simulated data. The metamodel covers a large range of hospital configurations and takes into account hospital resources, in terms of staff and infrastructures, operational efficiency and existence of an emergency plan, maximum capacity and behaviour both in saturated and over-capacitated conditions. The sensitivity of the model to different arrival rates, hospital configurations, and capacities and the technical and organizational policies applied during and before the strike of the disaster has been investigated. This model becomes an important tool in the decision process either for the engineering profession or for the policy makers. Copyright © 2010 John Wiley & Sons, Ltd.

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KEY WORDS: disaster resilience; hospital; metamodel; healthcare facilities; performance; resilience

INTRODUCTION

Recent events have shown how systems (regions, communities, structures, etc.) are vulnerable to natural disasters of every type, such as human errors, systems failures, pandemic diseases and malevolent acts, including those involving cyber systems and weapons of mass destruction (chemical, biological, radiological). Hurricane Katrina [1] clearly demonstrated the necessity to improve the local disaster management plans of different federal, state and private institutions. In order to reduce the losses in these systems the emphasis has shifted to mitigations and preventive actions to be taken before the extreme event happens. Mitigation actions can reduce the vulnerability of a system; however, if there is insufficient mitigation or the event exceeds expectations, recovery

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is necessary to have a resilient function for the community. Therefore, there is also the need for cost-effective mitigation of potential and actual damage from disruptions, particularly those causing cascading effects capable of incapacitating a system or an entire region and of impeding rapid response and recovery.

Healthcare facilities have been recognized as strategic buildings in hazardous events and play a key role in the disaster rescues; however, no attempt to practically relate the structural damage on the organizational aspects has been proposed so far. There is an extensive literature review (see in [2, 3]) in the definition of the main parameters of disaster resilience for healthcare systems and in the definition of the general framework, but no references have been found regarding the modeling and the measure of the organizational aspects of resilience. Indeed, organizational resilience is needed to evaluate the response of the community to hazardous events and to evaluate the real loss in terms of healthy population and quality of care provided.

In this paper, an organizational model describing the response of the hospital Emergency Department (ED) has been implemented. The model wants to offer a more comprehensive valuation of the multidimensional aspects of resilience.

TECHNICAL AND ORGANIZATIONAL RESILIENCE

The main purpose of this study is to relate the technical and organizational aspects of healthcare facilities to obtain a measure of organizational resilience that has not been attempted so far. The goal is to relate the *resilience index* to the *quality of care* provided and the eventual *loss of healthy population*, caused by the performance of the healthcare facility during the disaster.

Technical resilience is defined in Equation (1) as the integral of the normalized function $Q(t)$ indicating capability to sustain a level of functionality [4, 5], or performance over a control period

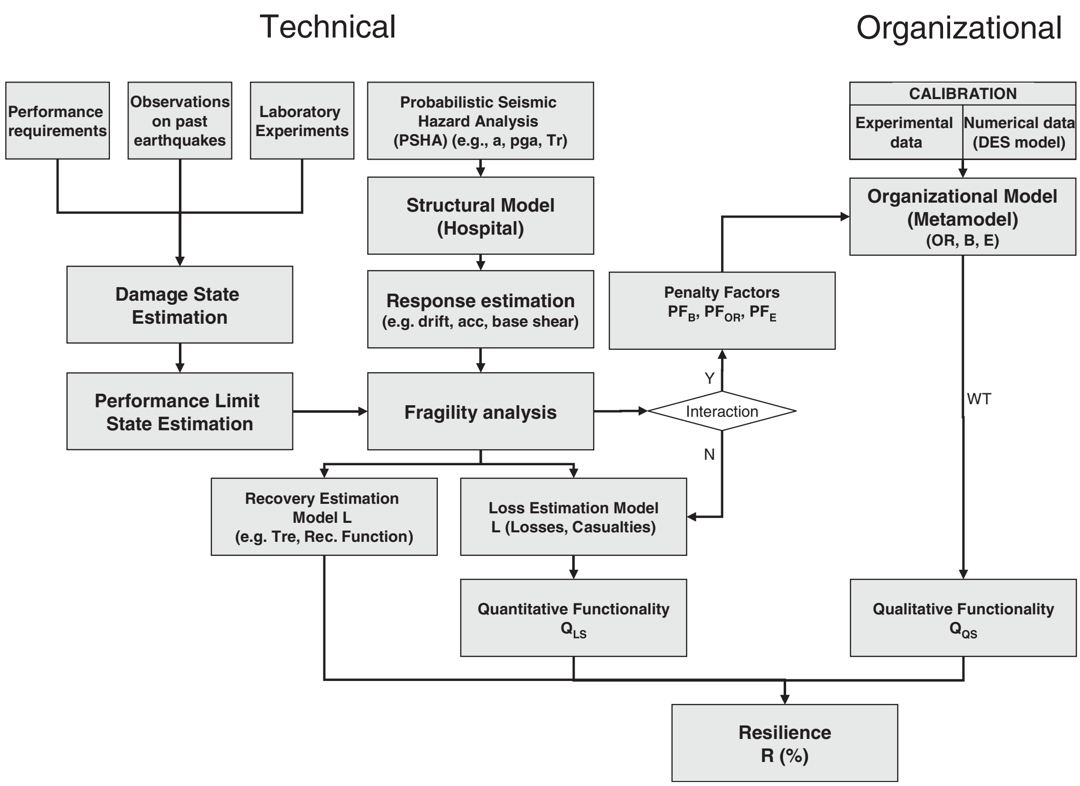

Figure 1. Resilience framework (MCEER approach).

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of time T_{LC}. In other words, it describes the ability to recover from disastrous events

$$R=\int_{t_{OE}}^{t_{OE}+T_{\mathrm{LC}}} Q(t)/T_{\mathrm{LC}}\,\mathrm{d}t \tag{1}$$

where t_{0E} is the instant of time from which the index is measured. Technical aspects are combined with organizational aspects and the formulation of organizational resilience for a hospital facility is provided using a hybrid simulation analytical model (called 'metamodel') that is able to describe the response of the ED during a hazardous event.

The system diagram in Figure 1 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 whereas the right part describes the organizational aspects to quantify resilience. The penalty factors (PF) that appear in the diagram describe the interaction between the technical and organizational aspects and their evaluation is discussed later in the paper.

FUNCTIONALITY OF A HOSPITAL

In order to define *resilience* it is necessary to define first the *functionality Q* of the hospital facility. In this paper, the functionality is defined as the combination of a *qualitative functionality* related to the quality of service (QS) and a *quantitative functionality* that is related to the losses in the healthy population.

Qualitative functionality in normal operating conditions

The qualitative functionality is related to the *QS* and it can be defined using the waiting time (WT) spent by patients in the emergency room (ER) before receiving care. The WT is the main parameter to evaluate the response of the hospital during normal and hazardous event operating conditions. Common sense, but also a relevant literature review reported in various references [6–8] indicates that functionality of a hospital is definitely related to the QS. Therefore if a measure of *QS* is found, then it is possible to measure the functionality Q of the healthcare facility. Maxwell [6] identified several multidimensional aspects of the *QS*. In particular six dimensions were suggested, such as the access to care, the relevance of need, the effectiveness of care, the equity of treatment, the social acceptability and the efficiency and economy. Each dimension needs to be recognized and requires different measures and different assessment skills.

In this study, the access to services is considered as the most important dimension to measure the *QS* in emergency conditions and it should be assessed in terms of ambulance response time and WT in the ED. Moreover, other researchers [7] pointed out the choice of the WT as an indicator of QS. Therefore, based on the references above, the qualitative functionality has been defined as

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

Equation (2) is a linear combination of two functions, $Q_{\mathrm{QS},1}$(t)and $Q_{\mathrm{QS},2}$(t), shown in Equation (3), while α is a weight factor that combine the two functions describing the behaviour in saturated and non-saturated conditions.

$$\begin{aligned} Q_{\mathrm{QS},1}(t) &= \frac{\max((\mathrm{WT}_{\mathrm{crit}}-\mathrm{WT}(t)),0)}{\mathrm{WT}_{\mathrm{crit}}} \quad \text{if } \lambda\leqslant\lambda_u \\ Q_{\mathrm{QS},2}(t) &= \frac{\mathrm{WT}_{\mathrm{crit}}}{\max(\mathrm{WT}_{\mathrm{crit}},\mathrm{WT}(t))} \quad \lambda>\lambda_u \end{aligned} \tag{3}$$

where all the following quantities are defined analytically later in the paper:

$\lambda(t)=$ arrival rate of patients at the hospital;
$\lambda_U=$ critical arrival rate of patients, when hospital reach the saturated conditions;

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WT_{crit} = critical waiting time at the hospital in saturated conditions, when $\lambda = \lambda_U$;
$WT(t)$ = waiting time when $\lambda = \lambda(t)$.

The qualitative functionality Q_{QS} is shown in Figure 2(a) for different weight factors.

Quantitative functionality in saturated conditions

In the literature the evaluation of the performance of the hospital in saturated condition is not considered, when the maximum capacity of the hospital is reached. In this latter condition, the hospital is not able to guarantee a 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} vs the total number of patients requiring care N_{tot}. In this case the loss is given by the number of patients who are not treated as follows:

$$Q_{LS}(t) = 1 - L(t) \tag{4}$$

where the loss function is defined by the normalized patients not treated.

$$L(t) = \frac{N_{NTR}(t)}{N_{tot}(t)} \tag{5}$$

The total number of patients requiring care, N_{tot}, and the total number of patients who do not receive treatment, N_{NTR}, are given by the following formula:

$$N_{tot}(t) = \int_{t_0}^{t_0+t} \lambda(\tau)\mathrm{d}\tau; \quad N_{NTR}(t) = N_{tot} - N_{TR}(t) = N_{tot} - \int_{t_0}^{t_0+t} \min(\lambda(\tau), \lambda_u)\mathrm{d}\tau \tag{6}$$

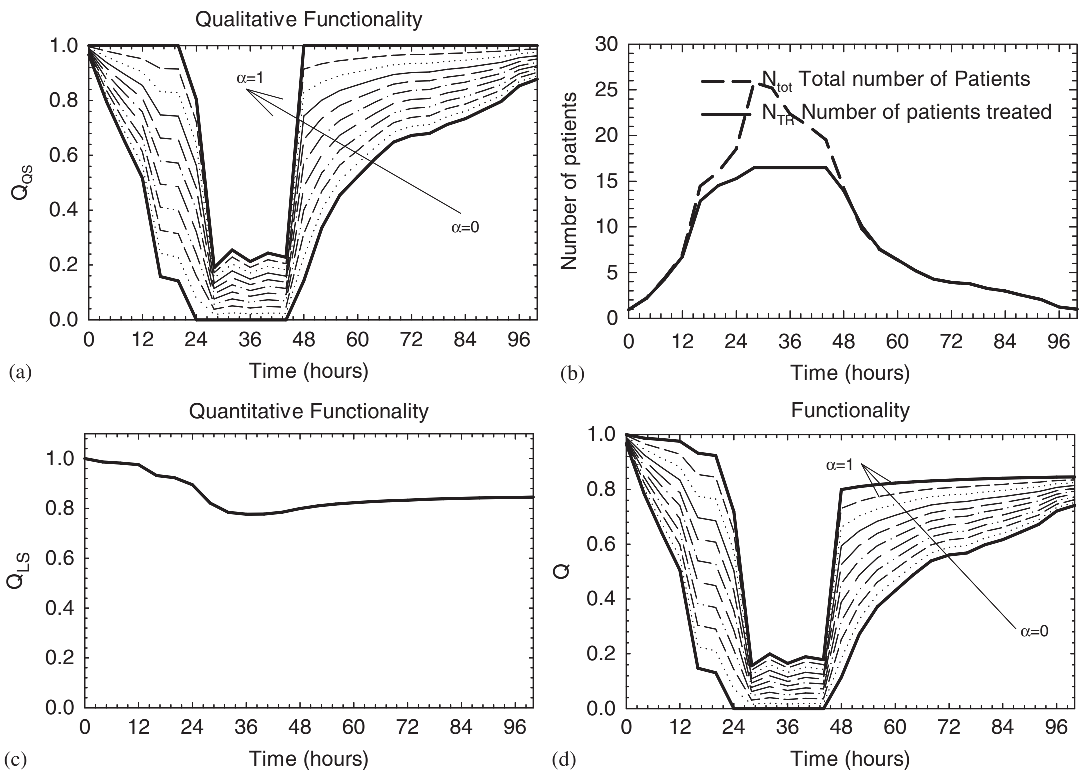

Figure 2. (a) Qualitative functionality for different α factors; (b) Number of patients treated; (c) Quantitative functionality (500 beds, 15 OR, and 1200 classes of efficiency); and (d) Combined functionality Q for different weighting factors.

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The quantitative functionality thus can be defined as

$$Q_{\mathrm{LS}}(t)=1-L(t)=1-\frac{N_{\mathrm{NTR}}(t)}{N_{\mathrm{tot}}(t)}=\frac{N_{\mathrm{TR}}(t)}{N_{\mathrm{tot}}(t)} \tag{7}$$

The number of patients waiting for care depends on the queue already present in the ER. Previous patients control the delay between their arrival and the treatment. A hospital is fully functional when it is able to absorb with minimum delay all the patients requiring care. When the number of patients waiting is higher than the number of patients treated (Figure 2(b)) the functionality decreases.

If the number of patients who can be treated is larger than the number of patients who arrive, then the quantitative functionality, Q_{LS}, is equal to one, because the capacity of absorbing the flow is higher than the actual arrival rate. If the treatment rate capacity is smaller than the arrival rate, the quantitative functionality takes a value smaller than one. An example of quantitative functionality, Q_{LS}, for a large size hospital (500 beds), high surgery capacity (15 operating rooms (OR)) and highest class of efficiency (1200 operations per OR per year) is shown in Figure 2(c).

Combined functionality

The total functionality, $Q(t)$, of the hospital that appeared in Equation (1) is given by the product of the two functionalities defined above

$$Q(t)=Q_{\mathrm{QS}}(t)\cdot Q_{\mathrm{LS}}(t) \tag{8}$$

Equation (8) is the first-order approximated combination of these two correlated quantities (higher terms should be considered for complete analysis). The combined functionality and the sensitivity to the weighting factor of the qualitative part, $Q_{\mathrm{QS}}(t)$, is shown in Figure 2(d). It is important to mention that both Q_{QS} and quantitative Q_{LS} functionalities require the estimation of the WT. The importance of parameter WT and its quantitative evaluation is described in the next paragraph.

WT AS MEASURE OF THE QS

The first issue to solve when approaching the problem of modelling of a healthcare system is defining the main parameter of response that can be used to measure the functionality of a hospital. A well-acknowledged study by Maxwell [6] has demonstrated that the WT in an ED may be used as a key parameter in the quantification of the QS in healthcare settings. 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.

Thompson *et al.* [9, 10] recognize that the WT is considered as an important determinant of patient satisfaction, which results from meeting or exceeding patient expectations, but providing information, projecting expressive quality, and managing WT perceptions and expectations may be a more effective strategy to achieve improved patient satisfaction in the ED than decreasing actual WT.

Later McCarthy's research [7] demonstrates that outpatient satisfaction with clinical treatment was not associated with WTs, but lengthy WTs in outpatient clinics are recognized as a challenge to the quality of care. WT is related to the hospital resources, in particular to those of the ED, such as stuff on duty, number of labs and OR, grade of utilization of the OR, and also to the degree of crowding [8] of the ED.

Richards *et al.* [11] point out the main factors that may influence the WT are: (i) the arrival mode, which is a statistically significant predictor (e.g. those who arrive by ambulance had the shortest WT); (ii) the hospital staffing characteristics (patient/physician ratio and patient/triage nurse staffing ratio), the race, ethnicity, payer source and (iii) the metropolitan location of the hospital, triage category, gender, age, arrival time. They pointed that the WT may affect the state of care of the patients already inside the hospital. When a disaster happens, in order to provide a higher availability of beds and staff to new patients, the emergency strategy of the hospital may

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involve the premature discharge of those inpatients whose conditions are considered stable, but who would have remained hospitalized in normal operational conditions.

Di Bartolomeo *et al.* [12] choose the pre-hospital time (PT) and the Emergency Department disposition time (EDt) as possible process indicators (PIs) for trauma care. This choice is based on the generally acknowledged principle that the time to receive care is an essential component of the survival chain. Short WTs improve outcomes, imply patients at higher risk where care is expedited all along the line and patients at lower risk where care runs naturally and easily fast. On the other side, long WTs worsen outcomes, imply patients at lower risk where care is slowed down, imply high-risk patients whose complexity inevitably prolongs time.

MODELING HEALTHCARE FACILITIES

DES model vs metamodel

Healthcare 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 healthcare 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 the literature to represent these complex hospital operations that are summarized in the MCEER report of Cimellaro *et al.* [3] . Among all, the discrete event simulation (DES) models are valuable tools for modelling the dynamic operation of a complex system, and in particular the emergency nature of a disaster can be easily incorporated in DES, for different types of hospitals. A DES model usually deals with p deterministic input parameters, defined over a feasible region, ψ, and q stochastic output variables such as

$$\psi = (\psi_1, \psi_2, \ldots\ldots, \psi_p) \overset{Y=Y(\psi)}{\longrightarrow} Y = (Y_1, Y_2, \ldots\ldots, Y_q) \tag{9}$$

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

$$\overline{\psi} = (\overline{\psi}_1, \overline{\psi}_2, \ldots, \overline{\psi}_q): \quad F(\overline{\psi}) = E[C(Y(\overline{\psi}))] \tag{10}$$

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

In Figure 3(a) is shown an example of a DES model of the ED of the Mercy Hospital located at Buffalo, NY, that has been build using visual simulator software developed by Promodel Corporation [14]. 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 provide more insights than DES models. A metamodel is a 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 later in Equation (37).

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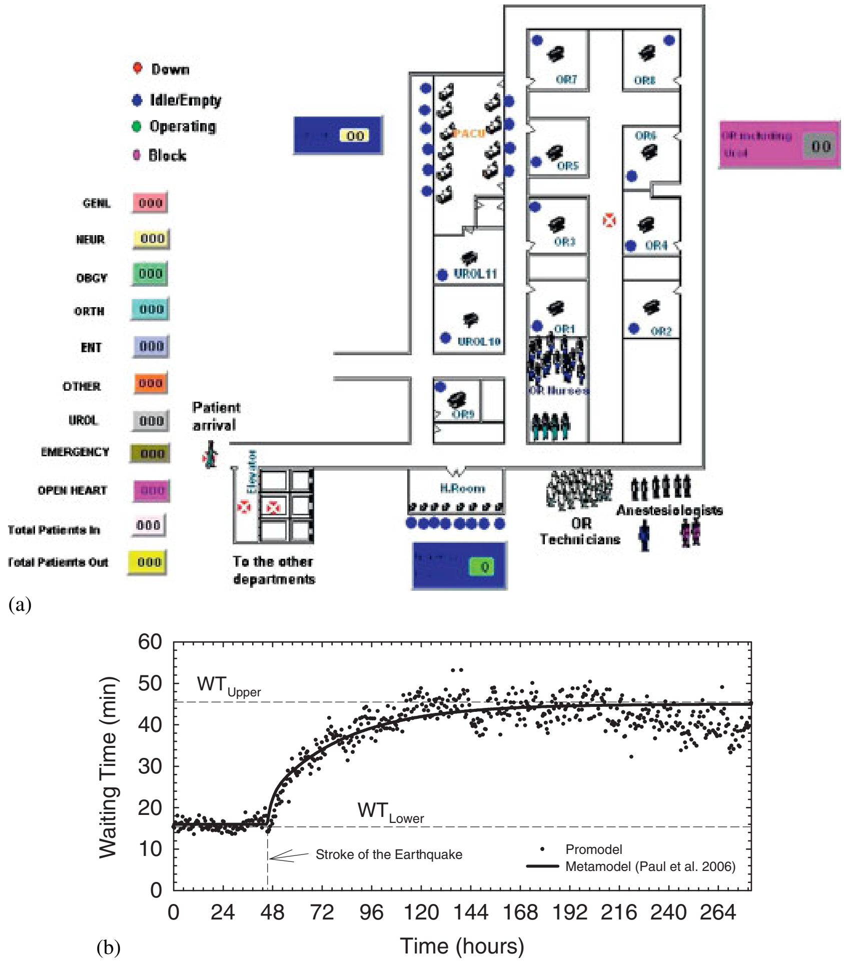

Figure 3. (a) Discrete event simulation model of the Mercy hospital in Buffalo, NY and (b) metamodel [13].

An example of the shape of this function is given in Figure 3(b), where the dots are the patient WT obtained from simulations with the DES model. The metamodel needs to be calibrated, and the first problem to handle when dealing with disaster is the lack of data. This deficiency [15] 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 the DES model.

ANALYTICAL CONSTRUCTION OF THE METAMODEL

In this paper the hospital functionality during a disaster is indicated by how quickly it can treat the injured patients, therefore it is directly correlated to the patient WT that is the response variable of the metamodel and it indicates how busy the hospital is. The mathematical formulation for the evaluation of WT is taken in analogy with the model of a manufacturing production line system in Yi [13], because the transient behaviour of the hospital during a disaster resembles that of a machine breakdown in a manufacturing production line. WT depends on internal and external organizational factors. The internal factors are the number of beds (B), the number of OR, the resources and staff productivity; the arrival rate λ and the patient mix α are the external input that can be defined as the percentage of patients who need the OR, which is the most critical resource

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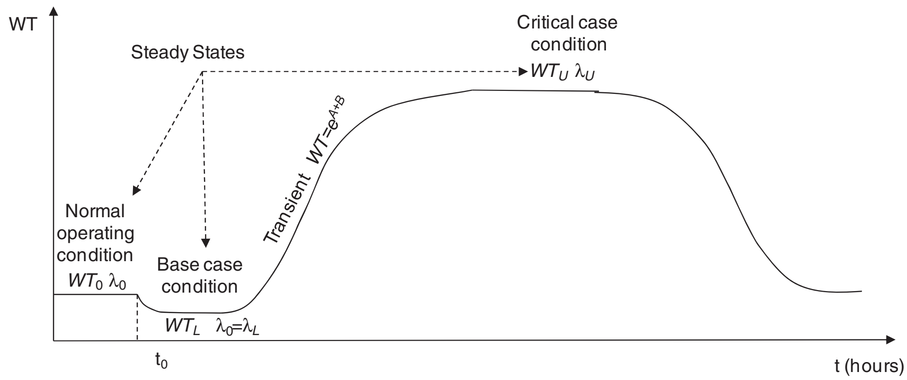

Figure 4. Metamodel during normal, base, and critical conditions.

in disaster condition. As regards the capacities of ER and Labs are assumed to be proportional to the size of the hospital (i.e. the number of beds), and are not direct input of the simulation model. The resources and staff productivity as well as the equipments/instruments are not modelled explicitly, but with the efficiency factor E which provides the number of surgeries per OR per year.

By combining the potentiality of off-line simulation runs and the capability of metamodelling to describe the transient behaviour of the system, a generic hospital model is built and calibrated, according to the ED patient volume, hospital size and operating efficiency considered. The metamodel obtained in this way is built in two steps:

1. *Off-line simulations* (normal condition). In this phase, the calibration of the parameters of the model is based on hospital steady-state behaviour (Figure 4) under constant arrival rate. The initial parameters of the model are usually provided by numerical simulations and national statistics. In particular, three steady-state conditions are considered:
   (a) *Normal operative condition*: It is the steady state in which the hospital copes with the normal arrival rate expected in a facility of that size, efficiency and normal duties of nurses, doctors, physicians and anesthetists.
   (b) *Base case condition*: It is the instant in which, after the disaster stroke, the hospital activates the emergency plan (EP), calls all the physicians and the nurses on duty and accedes to the emergency resources. It is assumed that there is a delay between activation of the EP and the highest flow of patients in the hospital, so it can be assumed that the arrival rate in the base condition is equal to the normal arrival rate, as well (Figure 4).
   (c) *Critical case condition*: It is the steady state reached by the hospital in saturated condition, in which all the resources are used and no further patients can be accepted. The hospital works at full capacity and it would be over capacitated with any additional input.
2. *Online simulations* during the disaster condition. In this phase, the results of the off-line simulation are used to built the response of the hospital in real time, when the disaster patient flow reaches the ED.

In the following paragraphs are explained in detail the three steady-state conditions of the off-line simulations and the steps to build the modified hospital metamodel.

Normal operating conditions

The *normal operating condition* also called *pre-disaster steady-state* condition is characterized by the pre-disaster average daily patient arrival rate under normal hospital operations λ_0 which is obtained from national statistics and by the pre-disaster average waiting time, WT_0, which is obtained from simulation data. The parametric form of quadratic nonlinear regression used for the

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arrival rate in normal operative condition is

$$\lambda_0 = const_0 + a_0 B + b_0 \mathrm{OR} + c_0 E + d_0 \alpha + e_0 B^2 + f_0 \mathrm{OR}^2 + g_0 E^2 + h_0 \alpha^2 + i_0 B\mathrm{OR} + j_0 BE + k_0 B\alpha + l_0 \mathrm{OR}E + m_0 \mathrm{OR}\alpha + n_0 E\alpha \tag{11}$$

where B is the number of beds, OR is the number of operating rooms, E is the efficiency of the hospital; α is the patient mix and $const_0$, a_0, b_0, a_0, b_0, c_0, d_0, e_0, f_0, g_0, h_0, i_0, l_0, m_0, n_0 are nonlinear regression coefficients obtained by the statistical analysis of national data that in our case study has been obtained from the state of California (http://www.oshpd.ca.gov/oshpdKEY/FindData.htm). The values of the coefficients used in Equation (11) are shown in Table AII (column 1) in the Appendix where it has been included the influence of the patient mix α. The value of the normal arrival rate depends on all the parameters considered in the metamodel. The parametric form of λ_0 in Equation (11) can be simplified using linear regressions, where the linear regression coefficients are evaluated on the basis of US statistical data [16] on ED visits prior to the disaster. The simplified expression is given in Equation (12) [13], and it depends only on the class size of the hospital

$$\lambda_0 = 6.1204 + 0.2520B \tag{12}$$

The pre-disaster average waiting time, WT_0, can be evaluated by the general parametric form of nonlinear regression, as shown in Equation (13)

$$\mathrm{WT}_0 = const_0 + a_0 B + b_0 \mathrm{OR} + c_0 E + d_0 \alpha + e_0 B^2 + f_0 \mathrm{OR}^2 + g_0 E^2 + h_0 \alpha^2 + i_0 B\mathrm{OR} + j_0 BE + k_0 B\alpha + l_0 \mathrm{OR}E + m_0 \mathrm{OR}\alpha + n_0 E\alpha \tag{13}$$

where the values of the coefficients used in Equation (13) are shown in Table AII (columns 2–6 and 8) in the Appendix for different conditions.

If a linear regression of Equation (13) is assumed [13], without considering the influence of the partial mix, the linear regression coefficients are given in Table AI where also the quality of fitting is indicated by the R^2 coefficient.

Base case conditions

The *base case condition*, also called *lower case*, corresponds to the instant in which, after the disaster stroke, the hospital activates the EP (Figure 4). The *base case* is characterized by the lower arrival rate during the disaster condition, λ_L, which is equal to the normal operative arrival rate, λ_0, and by steady-state mean value of waiting time, WT_L, in the system after a variation of initial conditions (e.g. calling all the staff on duty, applying an EP, reducing the quality of care and the time of care, etc.), under a given arrival rate equal to $\lambda_L = \lambda_0$. The parametric form of quadratic nonlinear regression used for the arrival rate in the base case condition λ_L is the same as in the normal operative condition that is shown in Equation (11). The WT_L is calculated for each hospital configuration, and it is given by the general parametric form of nonlinear regression, shown in Equation (13), but the coefficients of the nonlinear regression are obtained by statistical analysis of the data provided by the numerical simulations in Promodel, under a constant arrival rate equal to λ_0, but in disaster condition. Three different cases of nonlinear regressions are considered that are reported in Table AII. They correspond to the case when the patient mix α is not considered (columns 2 and 5 in Table AII) and when it is taken in account (columns 3, 4, 6 and 8) considering two levels of severity (2 and 3) that correspond to the ones reported in HAZUS.

Critical case conditions

The *Critical Case*, also called *Upper Case*, corresponds to the case when the system will become over capacitated with any additional volume and it is characterized by the maximum arrival rate,

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λ_U, that the hospital is able to handle. It corresponds to the maximum number of patients that the hospital can treat and the steady-state mean value of waiting time, WT_U, in the system after a variation of initial conditions, under a given arrival rate λ_U. These values are calculated for each hospital configuration, and they can be evaluated as well with the formulas of nonlinear regression given in Equations (11) and (13). The three sets of values of the regression coefficients and the value of R^2 are reported in Table AII and were obtained by statistical analysis of the data provided by the numerical simulations in Promodel. Three different cases of nonlinear regressions are considered and reported in the Appendix.

Modified continuous metamodel

As observed in the numerical simulation runs of the DES model, the higher the arrival rate, the longer it takes the hospital to reach a steady state after the earthquake. Therefore, under the base case condition (λ_L, WT_L), the hospital will take the shortest time to reach a steady-state condition while the opposite happens under the critical case condition (λ_U, WT_U). During the transient, when the system is shifting from a base to a critical case condition, the system will take a WT in between the boundary steady-state conditions (lower base case and upper critical case) (Figure 4). This assumption is true in non-saturated condition (with grade of utilization $\rho \leqslant 1$, where ρ is defined as ratio λ/λ_U), under the hypothesis that the arrival rate does not exceed the upper bound imposed by the critical case and therefore, it is assumed that the system is able to reach a new equilibrium, working at full capacity. The flowchart of the procedure to calibrate the dynamic model is shown in Figure 5.

The simulation results of Yi [13] show that WT grows nearly exponentially with the increase in arrival rate, therefore during the transient the WT is given by

$$\mathrm{WT} = \mathrm{e}^{A+B\lambda} \tag{14}$$

where the constants A and B are obtained by the boundary conditions. In the base case (or lower bound) and in the critical case Equation (14), respectively, becomes

$$\mathrm{WT}_L = \mathrm{e}^{A+B\lambda_L}; \quad \mathrm{WT}_U = \mathrm{e}^{A+B\lambda_U} \tag{15}$$

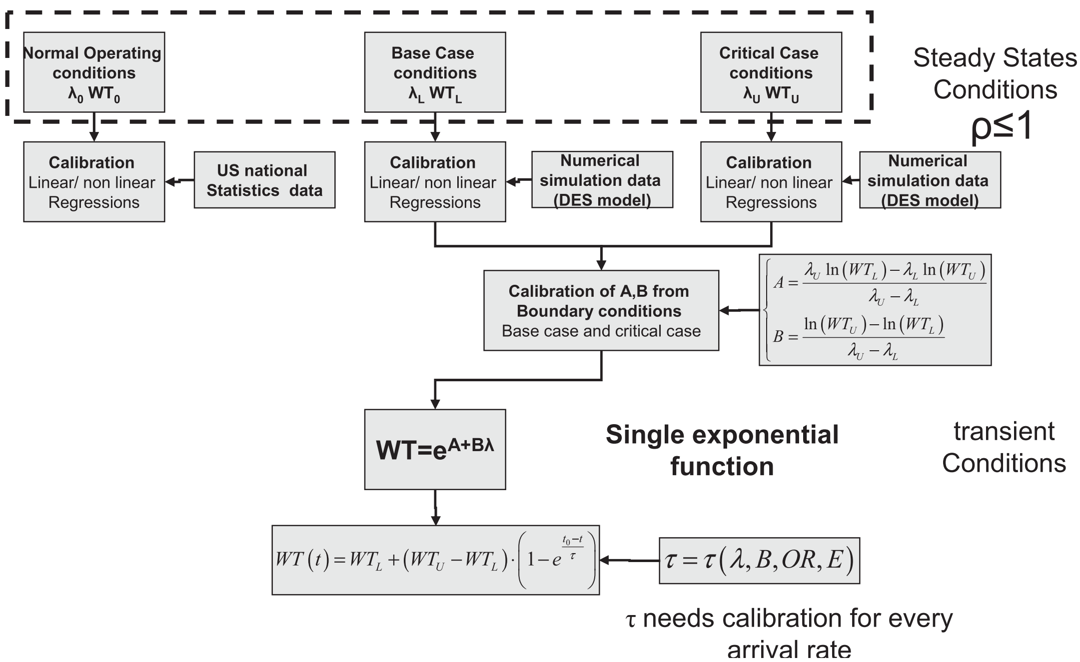

Figure 5. Flowchart of the calibration of the single exponential function.

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After some mathematical manipulations of Equation (15), the coefficients A and B are determined as

$$A=\frac{\lambda_U \log(\mathrm{WT}_L)-\lambda_L \log(\mathrm{WT}_U)}{\lambda_U-\lambda_L};\quad B=\frac{\log(\mathrm{WT}_U)-\log(\mathrm{WT}_L)}{\lambda_U-\lambda_L} \tag{16}$$

Back substituting the parameters A and B of Equation (16) in Equation (14) the following expression is obtained:

$$\mathrm{WT}(t)=\mathrm{e}^{\frac{\lambda_U \log(\mathrm{WT}_L)-\lambda_L \log(\mathrm{WT}_U)+(\log(\mathrm{WT}_U)-\log(\mathrm{WT}_L))\lambda}{\lambda_U-\lambda_L}} \tag{17}$$

that describes the exponential relationship between the WT and the arrival rate for any given hospital configuration where the parameters are obtained from regression analysis based on the two boundary conditions. Rewriting Equation (17), the WT during the transient is described by the following function, which holds for the system running between the base and the critical case

$$\mathrm{WT}(t)=\mathrm{WT}_L+(\mathrm{WT}_U-\mathrm{WT}_L)\cdot(1-\mathrm{e}^{\frac{t_0-t}{\tau}}) \tag{18}$$

where t_0 is the instant in which the disaster strikes, while τ is a time constant which depends on the time that the system takes to reach the steady-state condition. The constant $\tau(\lambda, B, \mathrm{OR}, E)$ depends on the time it takes the system to reach the steady state and it needs to be calibrated on a given hospital configuration (B, OR, E) and arrival rate λ (Figure 5). Although the single exponential function in Equation (18) describes the WT for a given hospital adequately, no common, underlying function that can represent a relationship between the time constant τ and arrival rate λ for all the hospital configurations exist (i.e. $\tau=\tau(\lambda)$). Therefore, instead of using a single exponential function, a double exponential function that allows generic modelling of transient WT is considered. The procedure to calibrate the double exponential function is described below, while a flowchart of the procedure to calibrate the function is shown in Figure 6. The constant τ for a given hospital configuration is different according to the arrival rate considered (λ_L and λ_U), and it is determined with the least square method of estimation. In particular, for the base case τ_L is determined such that

$$\begin{aligned}\text{minimize}\quad & F(\tau_L)=\sum_{i=1}^{n}[\mathrm{Wt}_{Li}-\mathrm{WT}_{Li}(\tau_L)]^2\\ \text{subjected to constraint}\quad & \tau_L\geqslant 0\end{aligned} \tag{19}$$

where Wt_{Li} is the waiting time obtained from the numerical simulations in the DES model with $\lambda=\lambda_L$, $\mathrm{WT}_{Li}(t)$ is the waiting time obtained from the analytical model in Equation (19) and n is the total number of points considered. Therefore, Equation (19) becomes

$$\mathrm{WT}_{Li}(t)=\mathrm{WT}_L+(\mathrm{WT}_U-\mathrm{WT}_L)\cdot(1-\mathrm{e}^{\frac{t_0-t}{\tau_L}}) \tag{20}$$

For the critical case τ_U is determined such that

$$\begin{aligned}\text{minimize}\quad & F(\tau_U)=\sum_{i=1}^{n}[\mathrm{Wt}_{Ui}-\mathrm{WT}_{Ui}(\tau_U)]^2\\ \text{subjected to constraint}\quad & \tau_U\geqslant 0\end{aligned} \tag{21}$$

where Wt_{2i} is the waiting time obtained from the numerical simulations in the DES model with $\lambda=\lambda_U$, whereas $\mathrm{WT}_{1i}(t)$ is the waiting time obtained from the analytical model in Equation (18).

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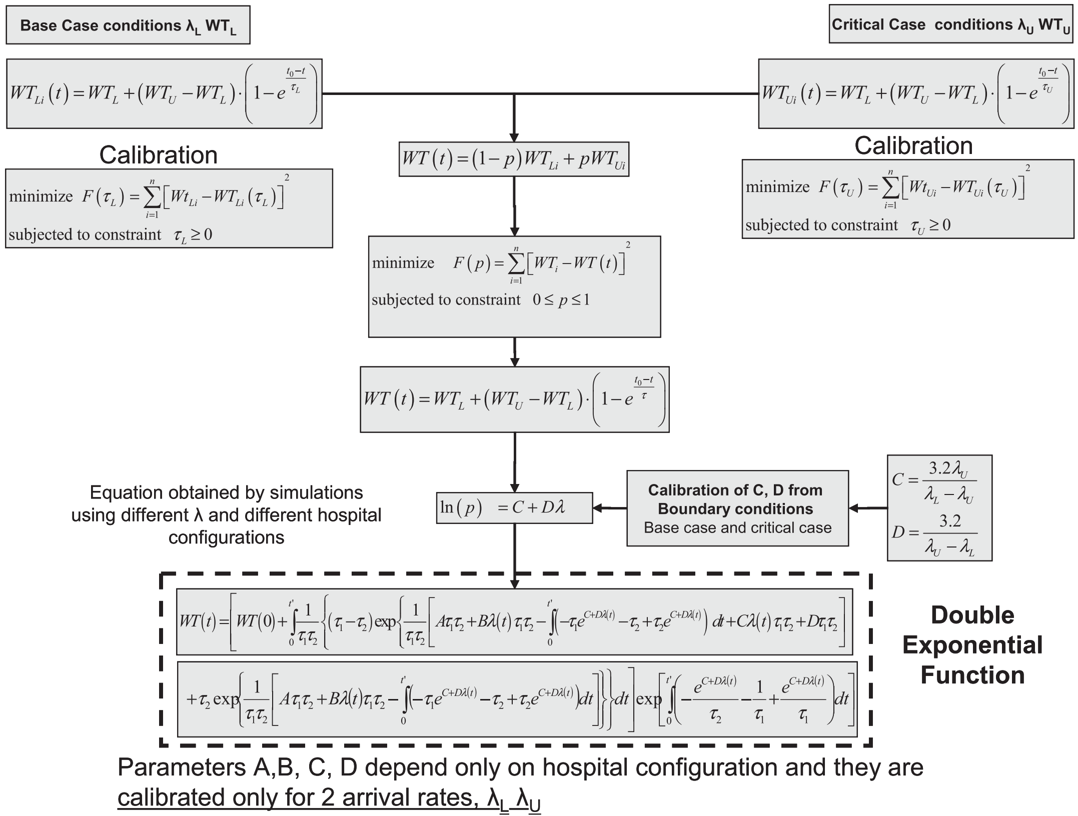

Figure 6. Flowchart of double exponential function ($\rho \leqslant 1$).

Therefore, Equation (18) becomes

$$\mathrm{WT}_{Ui}(t) = \mathrm{WT}_L + (\mathrm{WT}_U - \mathrm{WT}_L)\cdot\left(1 - \mathrm{e}^{\frac{t_0 - t}{\tau_U}}\right) \tag{22}$$

The final solution is built as a linear combination of the two exponential functions, with a weighting factor p that combines the *base case* and the *critical case* as follows:

$$\mathrm{WT}(t) = (1-p)\mathrm{WT}_{Li} + p\mathrm{WT}_{Ui} \tag{23}$$

and back substituting Equation (20) and (22) in Equation (23) the following expression is obtained:

$$\mathrm{WT}(t) = \mathrm{WT}_0 + (1-p)(\mathrm{e}^{A+B\lambda_U} - \mathrm{e}^{A+B\lambda_L})\cdot\left(1-\mathrm{e}^{\frac{t_{\mathrm{eq}}-t}{\tau_L}}\right) + p(\mathrm{e}^{A+B\lambda_U} - \mathrm{e}^{A+B\lambda_L})\cdot\left(1-\mathrm{e}^{\frac{t_{\mathrm{eq}}-t}{\tau_U}}\right) \tag{24}$$

The p factor is obtained from the least square method of estimation

$$\begin{aligned} \text{minimize} \quad & F(p) = \sum_{i=1}^{n} [\mathrm{WT}_i - \mathrm{WT}(t)]^2 \\ \text{subjected to constraint} \quad & 0 \leqslant p \leqslant 1 \end{aligned} \tag{25}$$

where WT is the transient waiting time at a given instant of time t given in Equation (24) and WT_i is obtained from numerical simulation runs or experimental data with different λ_i.

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Yi [13] found a relationship between the patient arrival rates λ and p, testing different hospital configurations that are given by the following logarithmic function:

$$\ln(p) = C + D\lambda \tag{26}$$

where C and D are the constants that need to be determined for a particular hospital. These coefficients can be determined using the 'base case' ($p=0$ and $\lambda=\lambda_L$) and critical case values ($p=1$ and $\lambda=\lambda_U$), for any specific hospital. When $p=0$, $\ln(p)$ does not exist, however Yi [13] showed that as p approaches 0, $\ln(p)$ approaches -3.2, therefore $\ln(0)=-3.2$ is used as satisfactory approximation in the calculation. Therefore from the boundary conditions for the *base case* and the *critical case* in Equation (26), the following coefficients are determined:

$$\text{base case} \quad \lambda=\lambda_L; \quad p=0; \quad C+D\lambda_L \approx -3.2 \tag{27}$$

$$\text{critical case} \quad \lambda=\lambda_U; \quad p=1; \quad C+D\lambda_L = 0 \tag{28}$$

Therefore

$$C = \frac{3.2\lambda_U}{\lambda_L - \lambda_U}; \quad D = \frac{3.2}{\lambda_U - \lambda_L} \tag{29}$$

Yi [13] also assumed that if the arrival rate is a continuous function of time namely $\lambda(t)$, then the transient WT of Equation (24) is given by the following equation expressed in discrete form:

$$\begin{aligned}\mathrm{WT}(t_i) = {} & \mathrm{WT}(t_{i-1}) + (1 - \mathrm{e}^{C+D\lambda(t_i)})(\mathrm{e}^{A+B\lambda(t_i)} - \mathrm{WT}(t_{i-1}))(1 - \mathrm{e}^{-\frac{t_1 - t_0}{\tau_1}}) \\ & + \mathrm{e}^{C+D\lambda(t_i)}(\mathrm{e}^{A+B\lambda(t_i)} - \mathrm{WT}(t_{i-1}))(1 - \mathrm{e}^{-\frac{t_i - t_0}{\tau_2}})\end{aligned} \tag{30}$$

Considering a small time interval Δt, and writing the derivative in discrete form the following expression is obtained after some mathematical calculations:

$$\mathrm{WT}(t) = \lim_{\Delta t \to 0}\left[\frac{\mathrm{WT}(t_i + \Delta t) - \mathrm{WT}(t_i)}{\Delta t}\right] = (\mathrm{e}^{A+B\lambda(t)} - \mathrm{WT}(t)) \cdot \left(\frac{1}{\tau_1} + \frac{1}{\tau_2}\mathrm{e}^{C+D\lambda(t)} - \frac{1}{\tau_1}\mathrm{e}^{C+D\lambda(t)}\right) \tag{31}$$

By integrating Equation (31) the following corrected continuous expression of WT is obtained:

$$\begin{aligned}\mathrm{WT}(t) = \Bigg[& \mathrm{WT}(0) + \int_0^{t'} \frac{1}{\tau_1\tau_2}\Bigg\{(\tau_1 - \tau_2)\exp\Bigg\{\frac{1}{\tau_1\tau_2}\Bigg[A\tau_1\tau_2 + B\lambda(t)\tau_1\tau_2 \\ & - \int_0^{t'}(-\tau_1\mathrm{e}^{C+D\lambda(t)} - \tau_2 + \tau_2\mathrm{e}^{C+D\lambda(t)})\,\mathrm{d}t + C\lambda(t)\tau_1\tau_2 + D\tau_1\tau_2\Bigg]\Bigg\} \\ & + \tau_2\exp\Bigg\{\frac{1}{\tau_1\tau_2}\Bigg[A\tau_1\tau_2 + B\lambda(t)\tau_1\tau_2 - \int_0^{t'}(-\tau_1\mathrm{e}^{C+D\lambda(t)} - \tau_2 + \tau_2\mathrm{e}^{C+D\lambda(t)})\,\mathrm{d}t\Bigg]\Bigg\}\Bigg\}\,\mathrm{d}t\Bigg] \\ & \exp\left[\int_0^{t'}\left(-\frac{\mathrm{e}^{C+D\lambda(t)}}{\tau_2} - \frac{1}{\tau_1} + \frac{\mathrm{e}^{C+D\lambda(t)}}{\tau_1}\right)\mathrm{d}t\right]\end{aligned} \tag{32}$$

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where WT(0) is the initial waiting time at time 0 and the coefficients A, B, C, D, τ_L and τ_U are all functions of the number of beds B, number of operating rooms OR, and the efficiency E. In saturated condition ($\lambda = \lambda_U$), the solution is equal to $\mathrm{WT}_{\mathrm{crit}}$, which is the maximum allowable WT under the maximum arrival rate feasible

$$\mathrm{WT}_{\mathrm{crit}} = \mathrm{WT}_L + \mathrm{WT}_U 1 - \mathrm{e}^{-\frac{T_{\mathrm{LC}}}{\tau_2}}) \tag{33}$$

where T_{LC} is the observation time. In particular for an observation time $T_{\mathrm{LC}} = \infty$, we have

$$\mathrm{WT}_{\mathrm{crit}} = \lim_{T_{\mathrm{LC}} \to +\infty} [\mathrm{WT}_L + \mathrm{WT}_U (1 - \mathrm{e}^{-\frac{T_{\mathrm{LC}}}{\tau_2}})] = \mathrm{WT}_L + \mathrm{WT}_U \tag{34}$$

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 [13].

The dynamic hospital model given in Equation (32) is valid only for the systems that are never over capacitated with $\rho \leqslant 1$. When $\rho > 1$ the equilibrium is not satisfied and the system is over-capacitated. During a disaster it can happen that the hospital has to cope with a long period of over-capacitated condition ($\rho > 1$), in which the assumption of steady-state condition is not valid. The ED can be compared with a production line chain and the overflow of patients in saturated condition can be associated to the effect of a sudden machine breakdown. This dynamic event in a multi-server machine assembly line will result in an increase in production time as well as the number of assemblies in the system. Similarly, it is assumed that when the hospital saturates it starts to work in steady-state condition and can process only a volume of assemblies (patients) given by the critical arrival rate λ_U. The processing time or WT for the compound assembly is then given by the sum of the steady-state time $\mathrm{WT}(t, \lambda = \lambda_U)$, and the disturbance $\Delta\mathrm{WT}(t)$, which represents the impact of the overflow ($\lambda - \lambda_U$) on the equilibrated condition $\lambda = \lambda_U$, and can be expressed by the following equation:

$$\mathrm{WT}(t) = \mathrm{WT}(t, \lambda = \lambda_U) + \Delta\mathrm{WT}(t) \quad \text{if } \lambda \geqslant \lambda_U \tag{35}$$

The first term can be calculated using Equation (32) with $\lambda = \lambda_U$, while the second term describes the over-capacitated condition, in which the inflow is greater than the outflow. In extensive form Equation (35) can be written as follows:

$$\mathrm{WT}(t) = \mathrm{WT}(t, \lambda = \lambda_U) + \left(\frac{\lambda(t) - \lambda_U}{\lambda_U} \right)_i \cdot (t - t_{\lambda_U}) \quad \text{if } \lambda \geqslant \lambda_U \tag{36}$$

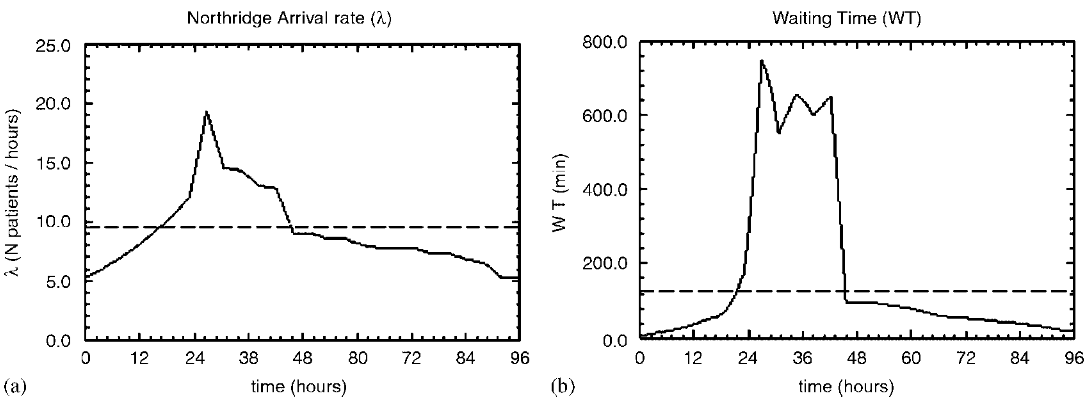

Figure 7. Response of the modified continuous metamodel under Northridge arrival rate.

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Therefore, the final expression of the WT for a hospital facility is given by

$$\mathrm{WT}(t) = \begin{cases} \text{Equation (32)} & \text{if } \lambda \leqslant \lambda_U \\ \mathrm{WT}(t, \lambda = \lambda_U) + \left(\dfrac{\lambda(t) - \lambda_U}{\lambda_U} \right)_i \cdot (t - t_{\lambda_U}) & \text{if } \lambda > \lambda_U \end{cases} \tag{37}$$

The modified continuous metamodel (MCM) in Equation (37) has been tested with different shapes of arrival rates in order to supply the reader about its dynamic behaviour.

When the hospital has to cope with an arrival rate beyond that which is able to cope with in saturated conditions, the WT increases proportionally to the difference between the actual arrival rate and the critical arrival rate (Figure 7). In this case, the hospital is not able to cope with the increased volume and it needs additional resources to be able to absorb all the patients.

INTERDEPENDENCIES BETWEEN TECHNICAL AND ORGANIZATIONAL RESILIENCE

Structural and non-structural damages cause reduction of functionality of the hospital at the organizational level. However, the hospital is affected more by non-structural damage than structural damage, because if water power and medical resources are damaged, they can render the hospital useless. MCM is able to incorporate the effect of structural and non-structural damages on the organizational model by incorporating a PF that is used to update the available ERs, OR and bed capacity of the hospital (Figure 1). Its value is determined by the fragility curve of each structural and non-structural components inside the hospital. Fragility curves are functions that represent the conditional probability in which a given structure's response to various seismic excitations exceeds given performance limit state [17]. The compact form assumed is given by

$$F_Y(y) = \Phi\left[\frac{1}{\beta} \ln\left(\frac{y}{\vartheta_y}\right)\right] \quad y \geqslant 0 \tag{38}$$

where Φ is the standardized cumulative normal distribution function , θ_y is the median of y and β is the standard deviation of the natural logarithm of y [18]. From fragility curves it is possible to evaluate PFs that are applied to all the internal parameters of the hospital (i.e. B, OR, E). The penalty factors PF_i for each structural or non-structural component are given by the linear combination of the conditional probabilities of having certain levels of damage. Four levels of damage are traditionally considered: P_1 slight, P_2 moderate, P_3 extensive and P_4 complete, which are obtained from the fragility curves provided for each structural and non-structural components. The total PF affecting each component analyzed is given by

$$\mathrm{PF}_i = a \cdot (P_1 - P_2) + b \cdot (P_2 - P_3) + c \cdot (P_3 - P_4) + d \cdot P_4 \tag{39}$$

where the coefficients a, b, c and d are obtained by normalized response parameters (e.g. drifts, accelerations, etc.) that define the thresholds of Slight, Moderate, Extensive and Complete damage states. For example if a drift sensitive non-structural component is considered, the coefficient a is defined as $a = \text{driftslight}/\text{driftcomplete}$. A complete list of damage state drift ratios for all building types and heights are provided in HAZUS [19].

The total penalty factor, PF_{tot}, affecting all the organizational parameters of the hospital is given by a linear combination of the individual PFs using weight factors obtained as ratio between the cost of each component and the overall cost of the building

$$\mathrm{PF}_{\text{tot}} = w_1 \mathrm{PF}_{\text{str}} + \sum_{i=2}^{n} \frac{(1 - w_1)}{n} \mathrm{PF}_i \leqslant 1 \tag{40}$$

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 factor of the non-structural

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components considered and n is the number of non-structural components. The proposed model incorporating facility damage can be used to identify the critical facilities, which would need increased capacities based on the casualties and it can be used to plan for any future expansion and reduction.

CASE STUDY: STATISTICAL HOSPITAL MODEL OF A CALIFORNIAN HOSPITAL

The hospitals of interest in disaster are those that treat all general types of injury and have ER and OR. Specialty hospitals (e.g. cancer and cardiac centers) are not considered to contribute significantly to the treatment of injuries resulting from a disaster. Therefore, only non-specialty hospitals are included in the formulation. In detail, the example shows a generic statistical hospital model, representative of a typical configuration of a Californian hospital (Figure 8). Three levels for each of the following parameters, the number of beds (B), the number of operating rooms (OR) and the efficiency (E) are used. They are

- Number of beds: small size = 100 B, medium size = 300 B, large size = 500 B;
- Number of operating rooms, OR: 5, 10 and 15;
- OR efficiency index E: 600, 900 and 1200.

A total of 27 combinations are possible, but small hospitals with a high number of OR, as well as large ones with low surgery capacity (only five OR) are considered as unfeasible combinations and were not taken in account, so in total 21 combinations were considered [3].

If we consider the California Statistics (http://www.oshpd.ca.gov/oshpdKEY/FindData.htm), the composition of healthcare facilities according to the size is reported in Figure 8.

The medium size hospital (300 beds) is the largest representative type; therefore these data partly justify the selection of the configurations in the case study.

The parameters of the metamodel are calibrated from the statistical analysis of data obtained on a set of simulation runs performed by Yi [13], using a DES model during the post-earthquake event. Regression equations are obtained for both pre-earthquake and post-earthquake WTs using average daily patient arrival rates calculated from national statistics and results are shown in Tables AI and AII in the Appendix.

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 ones used in this example. The choice of this earthquake intensity as a representative case study is not only dictated by the available data, but also with the fact that an average of 120 earthquakes per year worldwide in the magnitude range of 6.0–6.9 (like the Northridge and Kobe—17 January 1995—events) have occurred since 1900. For the past decade, the annual number of $M = 6.0 - 6.9$ shocks worldwide has ranged from 79 in 1989 to 141 in 1993. These numbers confirm that events like those affecting the urban areas of Northridge and Kobe are typical, and that we should be prepared for such shocks wherever cities and towns are located in seismically active areas [20].

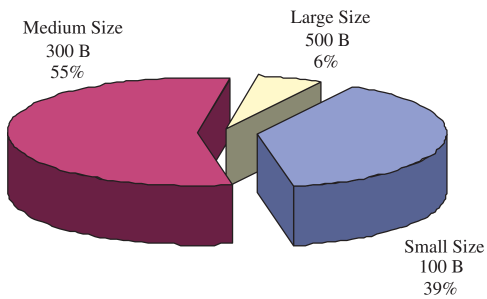

Figure 8. Composition of Californian hospitals.

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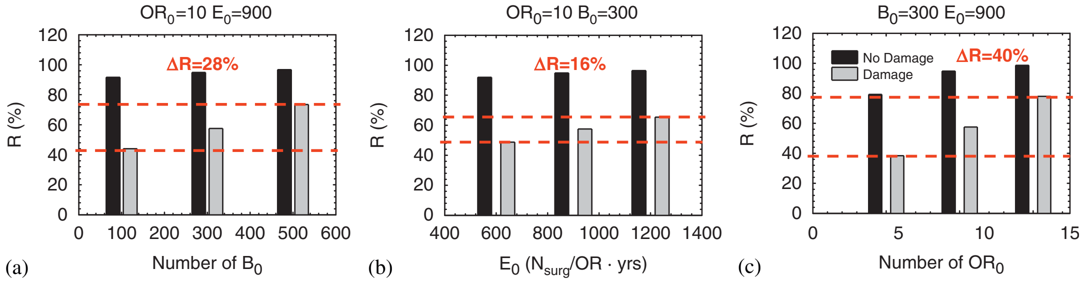

Figure 9. Increments of resilience index vs different internal parameters B, OR and E.

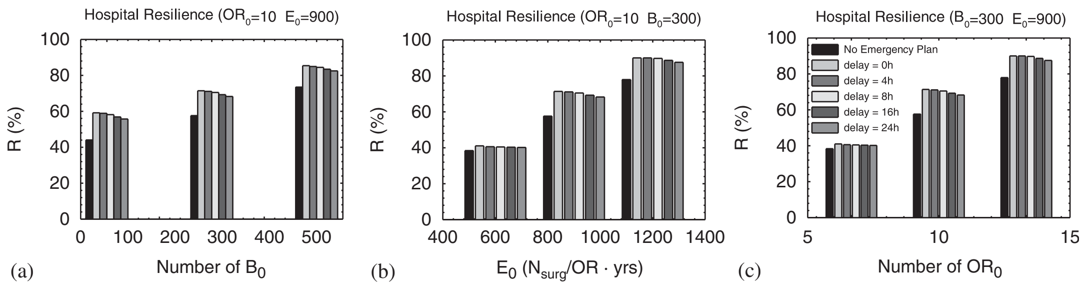

Figure 10. Sensitivity of the emergency plan.

In Figure 9 the sensitivity of resilience to the main parameters that characterize the organizational metamodel is investigated, while the weighting factor α used for the qualitative functionality in Equation (2) is set to 0.8.

In Figure 9(a) the efficiency ($E=900$) and the number of OR (OR $=10$) are kept constant, while the number of beds, B, 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 9(b)). On the other hand, Figure 9(c) 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 metamodel can consider also the capabilities of the staff and the existence of an EP during the disaster. 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 [21]. A large portion of in-patient can be discharged within 24–72 h in the event of mass casualty accident. 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 20–30%. The external shelters can provide additional room for the triage and first aid of the injured, reducing the pressure on the hospital, allowing the staff to concentrate on the non-ambulatory staff.

Triage and initial treatment at the site of injury, the so-called 'off-site patient care' [21] can relieve pressure on the emergency transportation and care system or when the local health care is damaged. It is assumed that doctors' skills may increase the efficiency of the hospital up to 20%. On the other side the existence of the EP, which can be applied with a certain delay, can increase the number of OR and the number of beds, respectively, of 10 and 20%.

In Figure 10 the effect of the application of the EP on the values of resilience has been investigated. It is assumed that the EP increases the number of beds of 10% and the surgery capacity (number of OR) of 30%. The values of the PFs before and after the application of the

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EP for the three size classes considered are reported in Table AIII in the Appendix. Resilience is plotted as function of the delay in the time of application of the EP, which acts as a sudden increase in the values of the organizational parameters (in this case number of beds and number of OR) with a certain delay from the stroke of the earthquake (0, 4, 8 or 16 and 24 h). The EP 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 10(c), where the performance in terms of hospital resilience increases up to 20%.

CONCLUDING REMARKS

The purpose of this study is to relate the technical and organizational aspects of healthcare facilities to obtain a measure of organizational resilience that has not been attempted so far. The resilience index is directly related to the quality of care, measured through the waiting time, and to the eventual loss of healthy population, caused by the performance of the healthcare facility during an extreme event. An organizational metamodel for healthcare facilities (e.g. hospitals) has been defined and implemented. This hybrid simulation/analytical model is able to measure the hospital capacity and the dynamic response of the hospital ED in real time using a single parameter: the WT before the service can be received. The WT is described using a double exponential function that has been opportunely modified to take into account the behaviour of the ED in over-capacitated conditions. Furthermore, the effect of damage of structural and non-structural components inside the hospital is incorporated in the organizational model using the penalty factors. 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 EP, maximum capacity and behaviour both in saturated and over-capacitated conditions. In order to show the methodology, an example of a statistical hospital model, representative of a typical Californian hospital has been implemented. The model has been calibrated on the only real data collected during the Northridge earthquake. The sensitivity of the model to different patients' 'arrival rates', 'patient mix', 'hospital configurations and capacities', and the technical and organizational policies applied during and before the strike of the disaster, has been investigated. Results based on the example show that for a medium size hospital of 300 beds the most significant way to improve the performance of the ED during a disaster is to increase the number of OR. The presence of an EP has a beneficial effect only in the case of medium and large size hospitals.

APPENDIX A

This appendix includes the coefficients of the non-linear regressions described in the paper (Tables AI–AIII).

Table AI. Coefficients of linear regression for WT_0 and WT_L without the influence of the patient mix α, WT_U and λ_U with the influence of the patient mix α [13].

Coeff	WT_0 w/o patient mix	WT_L w/o patient mix	Severity 2	
			WT_U	λ_U
const	13.0659	6.3000	136.4097	−0.0699
a	0.0067	0.0033	0.0533	0.0001
b	−3.4069	−0.4470	−9.7421	0.0124
c	0.0435	0.0010	0.0743	0.0001
R^2 (%)	0.82	0.72	0.61	0.95

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Table AII. Coefficients of nonlinear regression for λ_0, for WT_L without the influence of the patient mix α, WT_U and λ_U with and without the influence of the patient mix α [13].

	$\lambda_0=\lambda_L$ (Equation (11))	WT_U w/o patient mix mix α	Severity 2	Severity 2	WT_U w/o patient mix mix α	Severity 2		Severity 3	
			WT_L	WT_L		WT_U	λ_U	WT_U	λ_U
Coeff	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
const	−13.254	13930.287×10^{-3}	12.400	5.400	96.999	365.000	−137.000	434.000	−131.000
a	-53.900×10^{-3}	78.105×10^{-3}	−0.054	-37.300×10^{-3}	164.427×10^{-3}	−0.317	0.537	0.415	0.519
b	4545.700×10^{-3}	-5575.928×10^{-3}	−1.860	−0.957	-27633.186×10^{-3}	45.600	−8.610	66.000	−3.000
c	81.500×10^{-3}	16.679×10^{-3}	0.012	5.9×10^{-3}	267.850×10^{-3}	−0.283	0.248	−405.000	0.136
d	39.486×10^{3}	—	82.700	0.048×10^{-3}	—	−2147.000	-0.654×10^{-3}	−4585.000	-0.86×10^{-3}
e	0.200×10^{-3}	0.012×10^{-3}	0.050×10^{-3}	0.208	0.613×10^{-3}	-0.636×10^{-3}	−0.704	-1.980×10^{-3}	−1.150
f	-35.300×10^{-3}	336.647×10^{-3}	0.125	0.005×10^{-3}	2031.526×10^{-3}	0.360	-0.067×10^{-3}	0.000	-0.034×10^{-3}
g	-0.600×10^{-3}	-0.007×10^{-3}	0.060×10^{-3}	-3.380×10^{-3}	-0.062×10^{-3}	-0.054×10^{-3}	0.049	−1.240	0.056
h	-127.433×10^{6}	—	43.000	0.008×10^{-3}	—	6727.000	-0.142×10^{-3}	11.659	-0.046×10^{-3}
i	0.200×10^{-3}	-7.313×10^{-3}	0.070×10^{-3}	-1.200×10^{-3}	-49.692×10^{-3}	0.026	0.029	37.9×10^{-3}	29.800×10^{-3}
j	1.400×10^{-3}	0.300×10^{-6}	0.800×10^{-6}	279.000	-0.020×10^{-3}	0.160×10^{-3}	−1084.000	-0.053×10^{-3}	−2404.000
k	−141959.000	—	0.176	0.271	—	2.180	−1.630	2.06	−1.530
l	3.700×10^{-3}	-0.418×10^{-3}	0.378×10^{-3}	−15.900	-8.702×10^{-3}	-10.700×10^{-3}	4.400	-1.400×10^{-3}	6.500
m	1365.769	—	−9.860	0.029	—	−290.000	−1.030	−260.000	−0.842
n	125.783	—	0.013	30.200	—	1.870	1049.000	1.860	1342.000
R^2 (%)	0.85	0.90	87.8	89.5	0.80	70.2	98.3	74.8	98.5

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Table AIII. Penalty factors before and after the application of the emergency plan.

	Without EP			With EP		
B	PF_B	PF_{OR}	PF_{eff}	PF'_B	PF'_{OR}	PF'_{eff}
100	0.540	0.540	0.540	0.594	0.702	0.540
300	0.561	0.561	0.561	0.617	0.729	0.561
500	0.612	0.612	0.612	0.673	0.796	0.612

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