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Article

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Resilience of a hospital Emergency Department under seismic event

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Abstract

The article presents a new simplified model for measuring the resilience of a hospital Emergency Department during a seismic event. The waiting time is used as performance parameter which is first evaluated using a discrete event simulation model of the Emergency Department. Then, a metamodel has been developed from the results of the discrete event simulation model for different emergency codes considering the amplitude of the seismic input and the number of resources available right after the seismic event. Results show that when an earthquake occurs, generating a seismic wave of injured patients going to the Emergency Department, the maximum waiting time is approximately 13 h when an emergency plan is not applied. Instead, if the emergency rooms are not functional, due to earthquake damages, the waiting time increases dramatically and the Emergency Department is no more able to provide a proper service to the incoming patients. The proposed Emergency Department model can be used not only to evaluate the performance of existing hospitals during an emergency, but also to design the proper size of a new Emergency Department in a region.

Keywords

hospital resilience, metamodel, emergency department, discrete event model, health care facility

Introduction

Healthcare facilities are classified as strategic buildings because during extreme events they play a key role in the rescue operations and especially the Emergency Department (ED) that needs to provide immediate assistance to injuries. Even if the EDs are properly organized, a modification of the external environment due to a natural disaster can vary the patients' arrival rates and lead to a change in their performance that could end up in a poor service for all the patients (Davis et al., 2005). The "patients' satisfaction" can be measured using different parameters. Among them, the most representative parameter is the waiting time (WT) (Hamby and Fraser, 2004), which can also give an idea of how busy a hospital is, but it has been also recently used to measure the response and the capacity of a hospital during an emergency (Cimellaro et al., 2011). In this case, the performance of the ED is simulated using a *discrete event simulation (DES) model* which is a flexible and reliable tool usually adopted by healthcare decision-makers and managers to allocate and optimize the hospital resources. However, when an entire region and its hospital network need to be analyzed, the DES models become more complicated to use and time-consuming; therefore, in this article, it is described how to derive, from a complex simulation model, a simplified model called *metamodel* with a reduced number of parameters. Limitations apply, because the *metamodel* can be used under certain boundary conditions, but the advantage is that it can be implemented using a spreadsheet calculation (e.g. in excel) and it can be used by decision-makers who have to do quick, but reliable choices during an emergency. The proposed model can also be used in practice for prioritizing limited resources during emergency trying to reduce the WT (Luo and Liu, 2012). In the future, the idea is to extend the hospital model in an urban network while including also the travel time of patients arriving at the hospital (Bhaskar et al., 2011; Zeng and Zhang, 2013).

State-of-art

Several studies of healthcare systems have been published recently, and they are mainly focusing on patient routings and flow processes which are determinant to

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reduce the patient WT in the hospital (Hamby and Fraser, 2004). Different indicators have been used to measure the hospital performance (DesHarnais et al., 1988, 1990). Mainly numerical models are used, because their use is cheaper, faster, and less disruptive than manipulating the real-world system (Boxerman, 1996). In particular, DES has been widely used for modeling healthcare systems since the 1970s. Martin et al. (2003) studied the elder patients' admission into a Geriatric Department and different scenarios to reduce the WT. Van der Meer et al. (2005) analyzed a case study with the goal of reducing elective patients' WTs for the Department of Orthopedics. Only for a single specialty, they found that DES models are a good communication tool between hospital administrators and modelers. However, attempts to model entire hospitals are rare, because of the difficulty to represent the complexity of the hospital activities within a simulation model that must be simple (Pidd, 2003). Simplifying complex systems using proper assumptions is difficult; therefore, often only parts of the hospital are modeled (e.g. departments, clinics, etc.). Among them, the ED is a self-contained system with easily observable processes, so it is often modeled using DES models. For example, McGuire (1994) and Samaha et al. (2003) discussed the use of DES models to compare different alternative methods to reduce the hospitalization of patients.Takakuwa and Hiroko (2004) constructed a simulation model of the ED to observe the patients' flow and WTs. The reduction of patients' WT was made also by analyzing different "what-if" scenarios (Komashie and Mousavi, 2005). Davies (2007) developed a computer simulation in which the triage process was eliminated and a simplified service was obtained by eliminating queues between patients, which generally causes an increase in the WT.

Recently, Cimellaro et al. (2010) have developed a metamodel to study the performance of an ED following an earthquake. With respect to the 2011 model, the proposed one is able to distinguish between different codes (red, yellow, green, etc.), including also the intensity of the seismic input in the analytical model as additional parameter. Therefore, the proposed metamodel has a quadratic shape and not anymore the double exponential form presented in 2011. These improvements of the model have been possible due to the large availability of patient's data provided by a hospital located in downtown in Turin which has been used as case study in this example.

A new methodology for evaluating resilience of healthcare facilities

The term resilience is defined as the capacity of engineering and socio-economic systems to rebound after a severe disaster such as an earthquake (Cimellaro et al., 2010). A general resilience framework must consider both technical and organizational dimensions, which are interdependent (Cimellaro et al., 2014) each other. In literature, the concept of resilience has been applied both in the *short-term* period, for example, during hospitals' emergency, and in the *long-term* period, for example, during the reconstruction phase (Nejat and Damnjanovic, 2012). In this article, the organizational dimension of resilience R for an ED is evaluated using the following definition (Cimellaro et al., 2010).

Table 1. Percentage of patients arriving to the Emergency Department in both normal and emergency operating conditions.

Color code	Normal scenario (%)	Emergency scenario (%)	Number of patients
Red	0.56	3.70	21
Yellow	16.78	40.10	271
Green	71.19	48.48	224
White	11.47	7.81	43

$$R = \int_{t_{OE}}^{t_{OE}+T_{LC}} \frac{Q(t)}{T_{LC}dt} \tag{1}$$

where T_{LC} is the control time of the system and t_{OE} is the time of occurrence of event E. The functionality Q of the ED is dependent on the patient WT, so the following definition is proposed.

$$Q(t, n, \alpha) = \frac{WT(n, \alpha)}{\max\ (WT(n = n_{tot} - 1, \alpha))} \tag{2}$$

where n is the number of emergency room (ER); n_{tot} is the total number of ERs inside the ED; α is the amplification factor of the patient arrival rate; t is the given instant of time. The WT is evaluated for different color codes (red, yellow, green, and white) and is then combined together using weight factors p which are proportional to the distribution of the different codes during the emergency (e.g. Table 1), so the final expression is given by

$$WT = p_w \cdot WT_W + p_g \cdot WT_g + p_y \cdot WT_y + p_r \cdot WT_r \tag{3}$$

where p_w, p_g, p_y, and p_r are the weight factors of the white, green, yellow, and red code, respectively. For simplicity in equation (3), the dependency of the WT on time t, n, and α has been removed. Finally, the WT according to the different color codes has been defined as follows

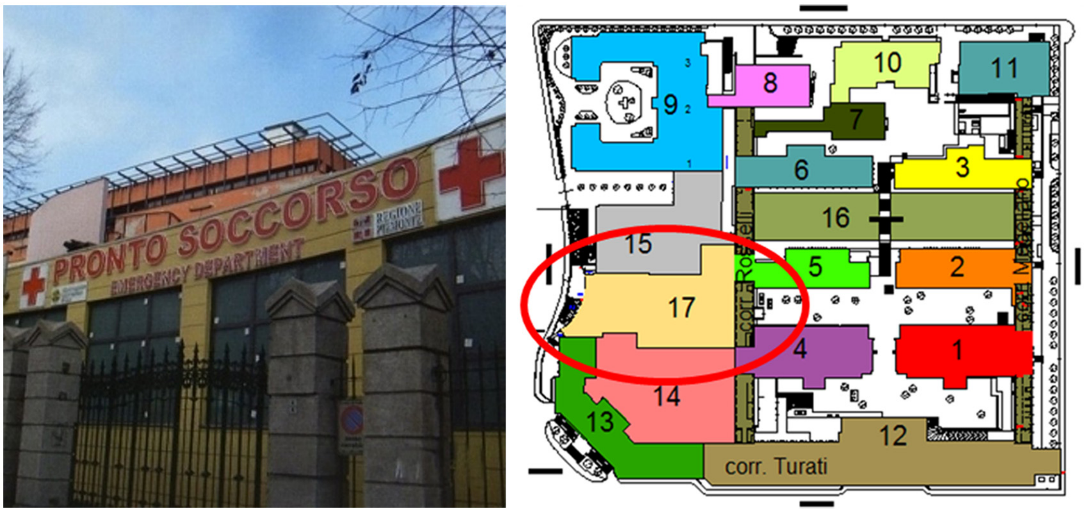

Figure 1. (a) Emergency Department of the hospital located in Turin and (b) plan view with the location of the ED within the hospital.

$$WT(t, n, \alpha) = WT_n(n)\left(\frac{WT_\alpha(\alpha)}{\max\ (WT_\alpha(\alpha = 1))}\right) \quad (4)$$

where WT_n and WT_α are the metamodels of the WT given later in the article, respectively, in equations (5) and (10).

DES model

Hospitals are complex dynamic systems where the organizational dimension is interdependent with the physical dimension at different levels. These interdependencies are more evident after extreme events like earthquakes when there is an increase in the patient flow and parts of the hospital might not be functional due to structural and non-structural damage, generating an interaction between the performance limit states of the different components (Cimellaro and Reinhorn, 2011). In these cases, typical performance indicators (e.g. the quality of treatment, the value of treatment, the WT, the patient expectation on emergency admission, etc.) might be difficult to measure and they might generate error in the evaluation of the system response. Several models are available in the literature to characterize these complex hospital operations that are summarized in a Multidisciplinary Center for Earthquake Engineering Research (MCEER) report (Cimellaro et al., 2009). Among all, the DES models are valuable tools for modeling the dynamic operation of complex systems, such as a hospital during an emergency situation. In particular, the use of DES models in combination with other models is becoming a common practice in several fields where new hybrid frameworks and architectures are presented (Alvanchi et al., 2011).

In this article, the DES model of an ED located in Turin, Italy has been developed to show the implementation issues of the proposed approach. The hospital has been selected due to the large availability of patient's data which has allowed developing a refined analytical model of the ED. The hospital is located in downtown and contains 17 units in total (Figure 1).

It was built in 1881, but several buildings were added during the twentieth century and nowadays, it covers an overall surface of 52,827 m^2. In this study, only the ED which is located in the building 17 has been modeled (Figure 1). Similarly to all EDs, the patients are divided in four color codes, according to the type of injury, using a procedure called "triage."*Red codes* (emergency) are patients with at least one of the vital functions compromised and their life is at risk. *Yellow codes* (urgency) have a partial impairment, but there is not an immediate risk for life. *Green codes* (minor urgency) have injuries that do not affect the vital functions while *White codes* (no urgency) are all patients who do not really need to be in the ED. Following this distinction, the ED itself is then divided into three main areas. An emergency area is located immediately in front, where the ambulance stops and contains two rooms in which the *red codes* are stabilized (Figure 2). In the parallel corridor, there is yellow and green codes' area, which contains five ERs. *White codes* are observed in their own ER, during the working hours; or they have to wait until yellow and green patients' ERs are available. Inside the ED, there are also recovery rooms in which the patients can rest before being discharged or sent in another part of the hospital (Figure 1).

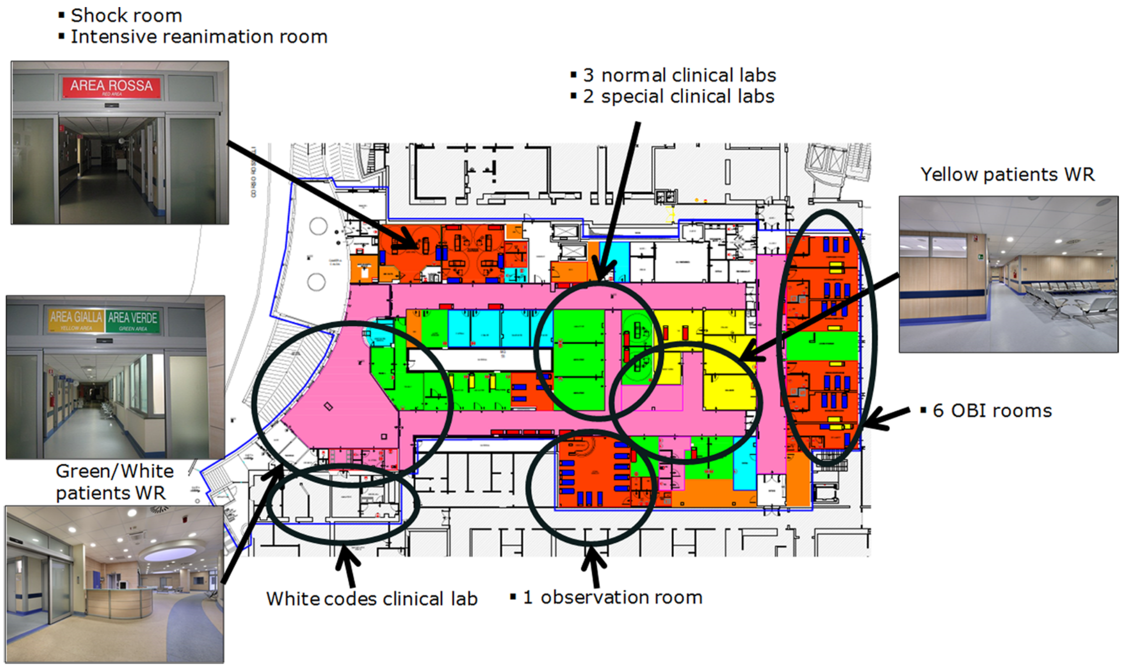

Figure 2. Distribution of the resources within the Emergency Department.

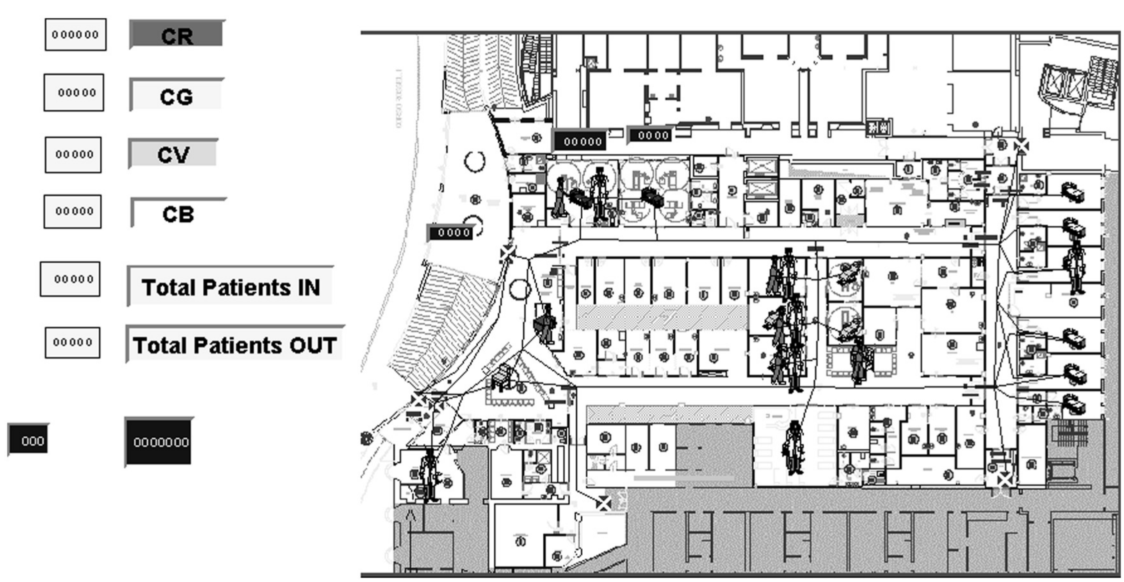

Figure 3. DES model of the Emergency Department, extract from ProModel software (Price, 1999).

A DES model has been developed to evaluate the performance of the ED during the emergency, which is shown in Figure 3. The model is implemented using a commercial software called ProModel (Price, 1999) and defining the parameters needed such as the *patients' arrival rate*, the *paths* through the ED, the *locations* (rooms) where patients are treated, the *processing times*, and the *procedures* that take place in each location, as well as all the *resources* involved (e.g. nurses, doctors, etc.).

The model has been analyzed using the patient arrival rate both in normal and emergency operating conditions right after the seismic event. Several assumptions have been made in the DES model to simplify the analysis of the ED. The main assumption is that the hospital structural and non-structural parts

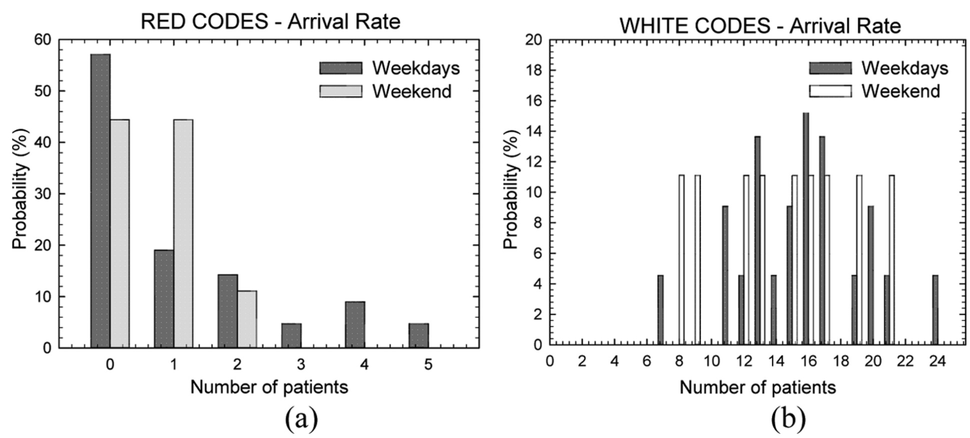

Figure 4. Probability of occurrence of patients' arrival rates divided into weekdays and weekend for (a) red code patients and (b) white code patients.

remain undamaged, so the difference between the normal operating conditions and the emergency operating conditions is based on a higher patients' arrival rate. Moreover, it is assumed that even after an extreme event, the organizational system remains the same, so there is no emergency plan in the ED. This is an unrealistic assumption because usually during an emergency, if there is an emergency plan, it is activated and the configuration of the system changes, but this option is not considered in this work. The current research wants to focus on how the system could react to an extreme event while remaining in normal operating condition mode, without changing the initial properties of the simulated model. Another assumption is that the patients are divided according to the code from the beginning, while in reality the injury code is determined once the patients have the first treatment at "triage." Moreover, the possibility to change the injury code during the treatment in the ED is also simulated; however, the code changes in the same point for all the codes during the analysis.

Input data analysis

The input data needed to calibrate the numerical model have been extracted by the hospital registers. They are the patients' arrival rate to the ED, the ED flow charts, the procedures inside the different rooms, as well as the personnel (known as resources) (Boginski et al., 2007) needed for each action.

The patients who arrive to the ED have been divided according to their code and their respective arrival rates (Yi, 2005) have been determined. Figure 4 shows the arrival rate for two types of code, known as the probability of having a fixed number of patients arriving during the day, divided by the injury codes and in weekdays and weekend.

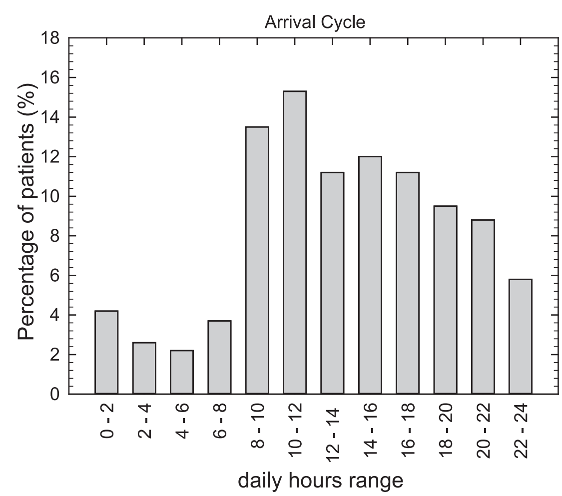

Figure 5. Patient daily arrival cycle.

The distribution of the patients' arrivals in a day is defined by the arrival cycle (Figure 5) which represents the percentage of daily patients who arrive at a given instant of the day.

The patients' flow chart was determined both by interviews with personnel and by hospital statistical data. The different paths that a patient could follow after entering in each room are determined. Then, it is possible to determine the percentage of patients following a certain path in the ED or that modify their emergency code due to a progress or exasperation of their injury, by analyzing the hospital statistics data. The resources involved in each process as well as the time table of the personnel are also used to extract the calibration data. In summary, the resources employed and simulated in the ED are seven doctors, nine nurses, four assistants, and two health workers.

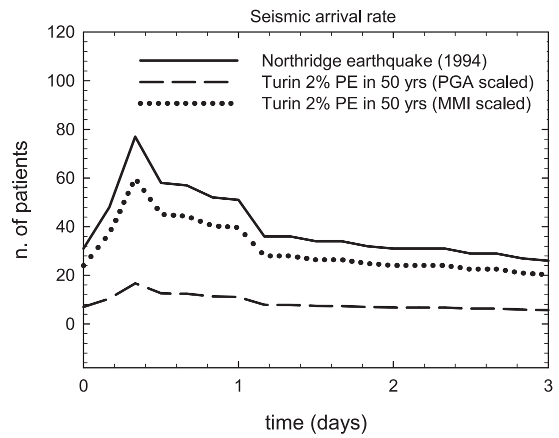

Figure 6. Arrival rates for Northridge earthquake and arrival rate scaled with respect to PGA and Modified Mercalli Intensity.

Patient arrival rate seismic input

The data used as input in the model is the *patient arrival rate* collected in a Californian hospital during 1994 Northridge earthquake. The pattern of the Northridge arrival rate is given in the paper of Cimellaro et al. (2011); however, the arrival rate in this article has been scaled to adjust to an earthquake with a return period of 2500 years, assuming a nominal life for a building of strategic importance of 100 years according to the Italian seismic standards (NTC-08, 2008). Therefore, the patient arrival rate was first scaled using the peak ground acceleration (PGA) corresponding to the location of the Mauriziano hospital in Turin (Figure 6). However, the scaling procedure based on the PGA has some limitations, because it does not take into account the population density and the urbanization level, which represents an important index for the evaluation of the effect of an earthquake and for the calculation of the number of patients arriving in a hospital.

Therefore, a second scaling procedure based on the Modified Mercalli Intensity (MMI) scale was selected, because it takes into account all the features mentioned above. In fact, the MMI scale ranges from I (no felt) to XII (total destruction) and it is able to quantify the direct effects of an earthquake in terms of human lives and structural damage. Figure 6 shows the plot of Northridge arrival rates in a 3-day window, but opportunely scaled with respect to the ratio between the PGA and the MMI values to obtain the corresponding arrival rate in Turin. The patient arrival rate of Northridge earthquake was selected, because it is the only documented event (McArthur et al., 2000; Peek-Asa et al., 1998; Stratton et al., 1996) where patient arrival rate was collected. In fact, data collection during an emergency such as an earthquake is a low priority activity, so it is very difficult to find real data. Then, the seismic arrival rate was divided into different color codes following a similar distribution proposed by Yi (2005) shown in Table 1.

Simulation results of the DES model

The indicator that has been used to evaluate the response of the ED is the WT which is the time the patients wait before being treated. First, the model has been run in normal operating conditions and has been calibrated by comparing the real data given by the hospital staff with the numerical results obtained by the simulations (Figure 7).

After the calibration of the model, Monte Carlo simulations were run by performing 13-day simulation several times in order to collect enough data to approach the problem statistically. The average WT is plotted in Figure 8, for yellow, green, and white codes, respectively, where it is shown that the WT increases when the earthquake strikes and goes back to the initial value after 3 days of emergency period.

Metamodel

The DES model that has been built is a simplification of the real-world system and gives an idea of how complex the ED is. Although the DES models are valuable

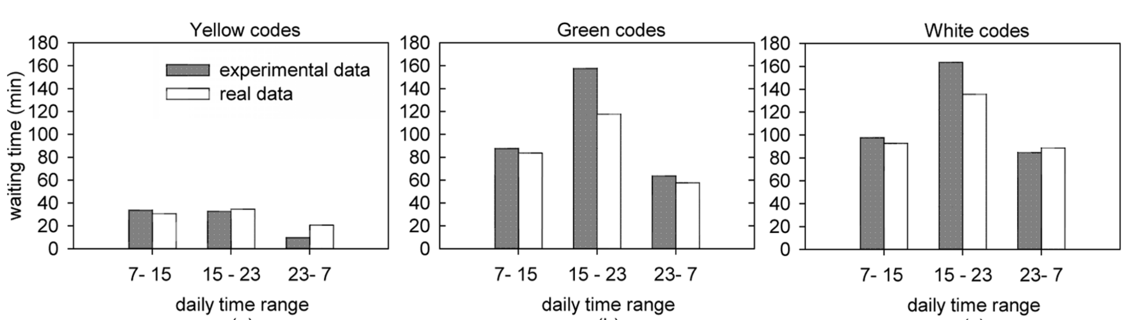

Figure 7. Comparison of real versus experimental simulated data for (a) yellow codes, (b) green codes, and (c) white codes.

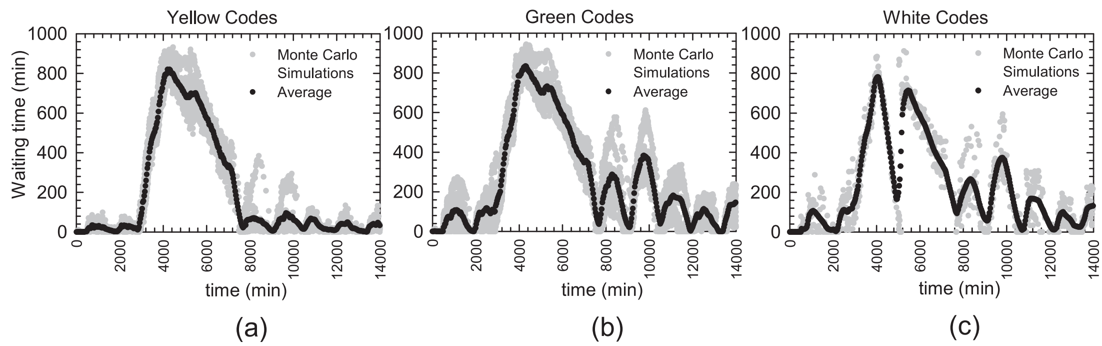

Figure 8. Waiting time for (a) yellow codes, (b) green codes, and (c) white codes, under seismic input.

tools for hospital modeling, they face many challenges. First, they are time-consuming because they require multiple analyses to have statistically acceptable results. Furthermore, it is often necessary to model a network of hospitals to perform simulation at regional level, especially when the resilience of a region affected by an earthquake wants to be evaluated. In this case, it is necessary to run multiple analyses on multiple hospitals to estimate the network capacity, but the DES models are computationally demanding. For these reasons, there is a need to create a simpler model, called *metamodel*, whose purpose is simulating the ED using a reduced number of variables which can be integrated with less effort into other decision support systems.

The parameters of the metamodel must be correlated to the hospital characteristics, such as the *number of beds, the number of doctors*, the *efficiency* of the ERs, and so on. The current research is proposing a metamodel which can distinguish between the various color codes, improving previous existing models (Yi, 2005), which are based on a single type of patient for the ED. The main output parameter is the WT. Several scenarios have been considered which can be grouped based on the amplitude of the seismic input and the level of damage of the ED which is described by the number of non-functional ERs. Finally, two equations for the ED have been proposed which have been determined using curve fitting procedures.

Since there are no historical data of the ED under emergency, a sensitivity analysis is used not only for calibrating the simulations, but also for estimating the aleatoric uncertainties of the variables in the model. First, a sensitivity analysis has been performed by closing the ERs one by one (n), assuming that the structural damage in the ER makes them non-functional. The increase in the WT for the yellow codes due to the closure of n ERs is shown in Figure 9. Figure 9 shows that by closing the ERs, the WT increases and in particular for $n = 2$ and $n = 3$, the WT curves are very close. This behavior can be explained because one of the ERs is open only some hours a day during

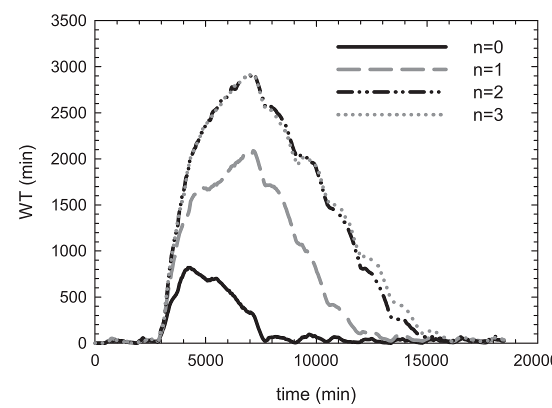

Figure 9. Waiting time of the yellow code in the DES model for different damage states where *n* is the number of non-functional emergency rooms.

weekdays and it is closed all day during the weekends, so its presence does not affect the WT of the yellow codes. After fitting different equations to the data shown in Figure 9, the following equation has been selected

$$WT_n(t, n) = \frac{1}{a(n) + b(n)t^{2.5} + (c(n)/t^2)} \tag{5}$$

with

$$a(n) = \frac{1}{-444.55522 - 3725.6162n} \tag{6}$$

$$b(n) = \frac{1}{9.5429351 \times 10^{11} + 7.354141 \times 10^{12}n} \tag{7}$$

$$c(n) = \frac{1}{2.3885795 \times 10^{-5} + 3.0610773 \times 10^{-5}n} \tag{8}$$

where $WT_n(t, n)$ is the WT in minutes, t is the time in minutes, and n is the number of non-functional ERs. The comparison between the numerical results and the analytical model is shown in Figure 10. By observing

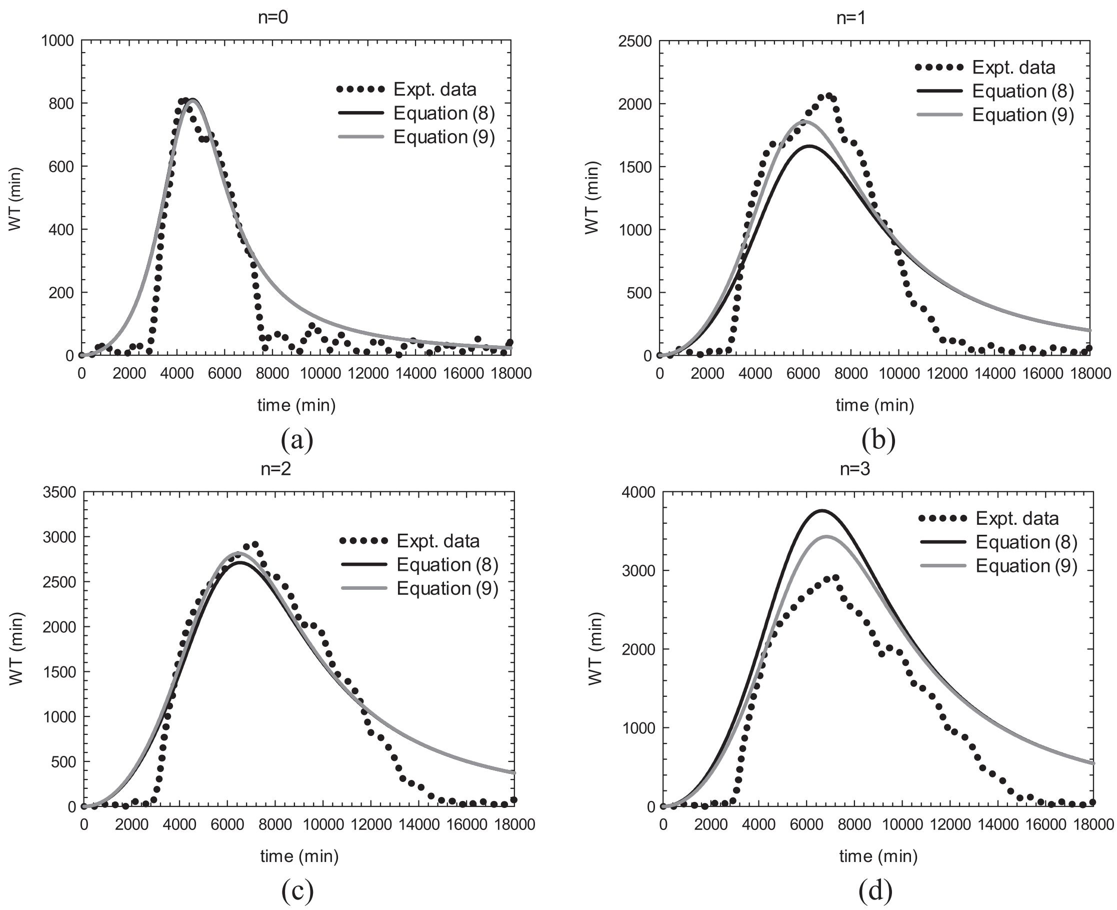

Figure 10. Experimental data versus equation (4) using the parameter $c(n)$ in equations (8) and (9), for (a) $n = 0$, (b) $n = 1$, (c) $n = 2$, and (d) $n = 3$.

Figure 10, the model in equation (5) using the parameter $c(n)$ in equation (4) has a good fitting for all the n values except for $n = 3$. As aforementioned (Figure 9), for the value of $n = 2$ and $n = 3$, the WT curves for the experimental data are very similar. When fitting the parameter $c(n)$ in equation (8), a difference between the experimental values and the analytical model is observed which brings to overestimate the experimental values for $n = 3$. Therefore, another equation for the parameter $c(n)$ has been proposed in order to minimize these discrepancies

$$c(n) = e^{9.1144666 + 1.5318346 \times e^{-n}} \tag{9}$$

The results of the model in equation (5) using the parameter $c(n)$ in equation (9) are also shown in Figure 10. The comparison of the $WT(t, n)$ for both equations shows that equation (9) fits better for $n = 1$ and $n = 2$ although for $n = 3$ there are still some divergences between the simulated values and the analytical model.

Table 2. r^2 values of equation (10) for different earthquake intensities.

Scaling factor α	r^2
1.0	0.9977
1.1	0.8384
1.2	0.8305
1.3	0.8524
1.4	0.8577
1.5	0.8840
1.6	0.9919

Sensitivity of the WT to the seismic input

The seismic input has also an impact on the patient WT that needs to be analyzed in detail. The seismic arrival rate has been amplified proportionally performing an incremental dynamic analysis (IDA) using the seismic arrival rate given in Figure 6. The scaling factors adopted for the analysis are listed in Table 2. Monte Carlo simulations have been performed and the

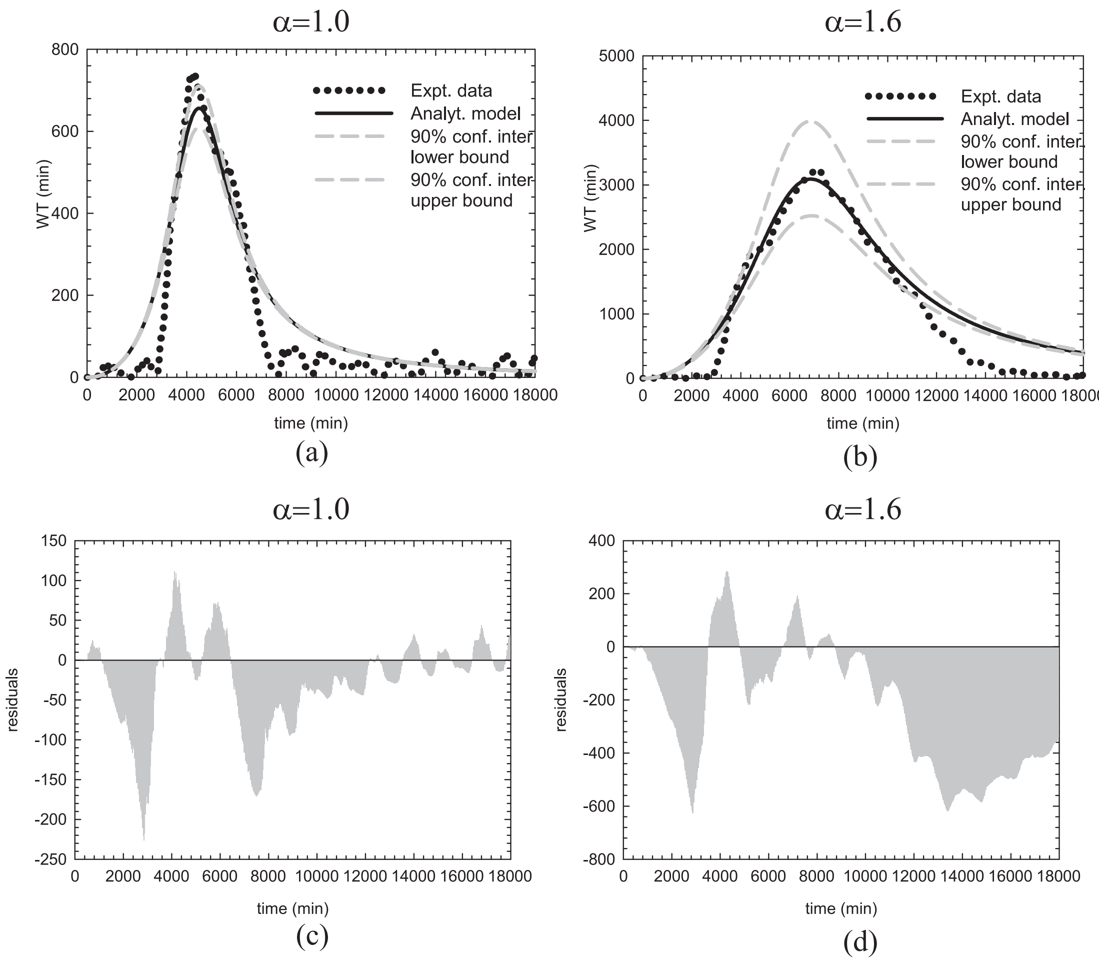

Figure 11. Experimental data versus analytical model for (a) α = 1.0, (b) α = 1.6, and (c, d) residual plots.

average WT for each scaling factor has been considered as target for the analytical model used to fit the experimental results.

The proposed analytical model is the following

$$WT_{\alpha}(t,\alpha) = \frac{1}{d(\alpha) + e(\alpha)t^{2.5} + (f(\alpha)/t^2)} \tag{10}$$

with

$$d(\alpha) = \frac{1}{(-130662.61/\alpha) + 354373.19 \times e^{-\alpha}} \tag{11}$$

$$e(\alpha) = \frac{1}{(2.8903288 \times 10^{14}/\alpha) - 7.8398432 \times 10^{14} \times e^{-\alpha}} \tag{12}$$

$$f(\alpha) = e^{8.9580246 \ln \alpha + (10.938463/\alpha^{1.5})} \tag{13}$$

Equation (10), with its 90% confidence interval bound, and the residuals plots for the scale factors $\alpha = 1.1$ and $\alpha = 1.6$ are shown in Figure 11. The r^2 values of equation (10) for the different scaling factors of the seismic input show good agreement with the experimental data as shown in Table 2.

Finally, the analytical WT model given in equation (10) is shown in Figure 12 for the different amplification factors of the seismic input.

For all the different α values, the error between the experimental data and the analytical model at the peak value is given in Table 3.

The highest error at the peak is 20.55% obtained for $\alpha = 1.6$, but in general the proposed metamodel shows good agreement with the experimental results.

Simulation results of the metamodel

The metamodels proposed in the previous paragraph are then combined using equation (4). The comparison of the WT for different number of ERs closed and for different intensity of the seismic input is shown in Figure 13.

By applying equation (2), using the numerical result of both the DES model and the metamodels provided

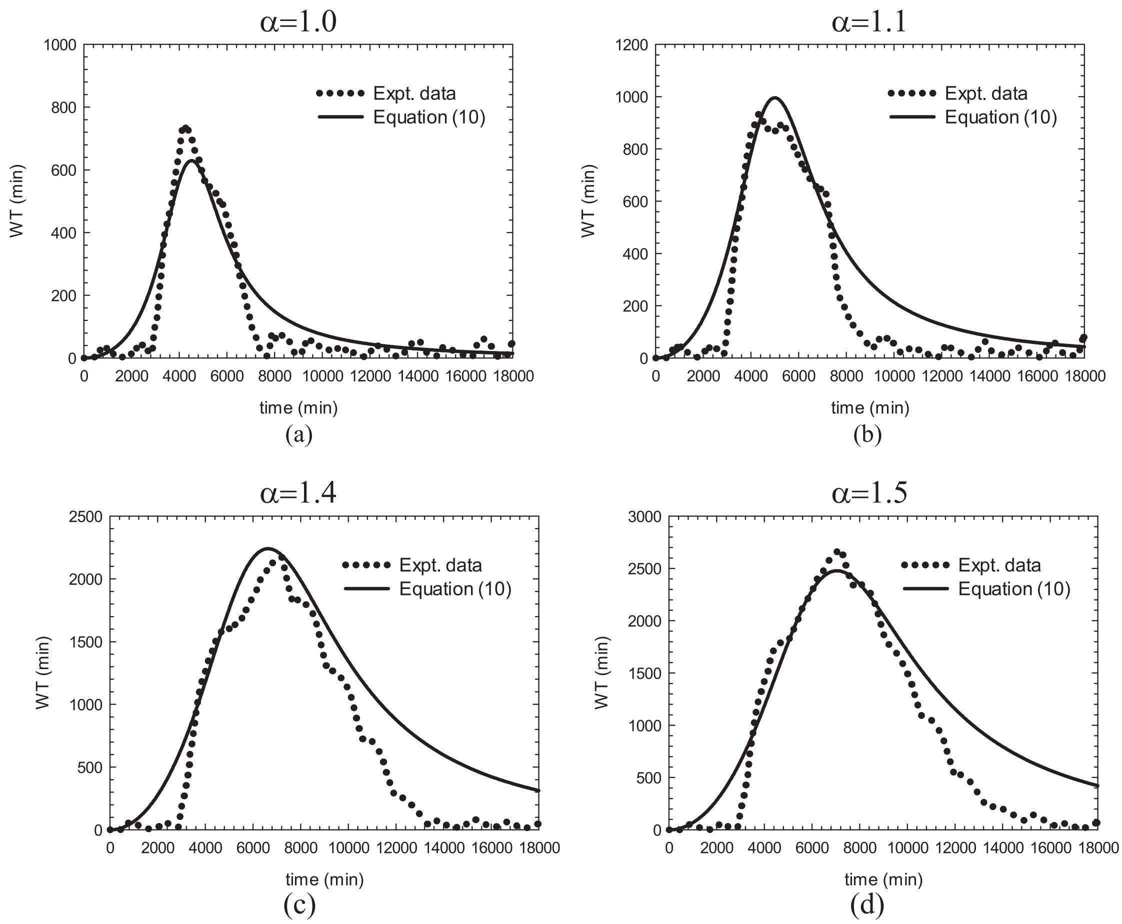

Figure 12. Experimental data versus equation (10) for (a) α = 1.0, (b) α = 1.1, (c) α = 1.4, and (d) α = 1.5.

Table 3. Error between the experimental and analytical model in equation (10) evaluated at the peak value.

Scale factor α	Error (%)
1.0	17.27
1.1	4.60
1.2	17.68
1.3	8.48
1.4	0.81
1.5	7.97
1.6	0.55

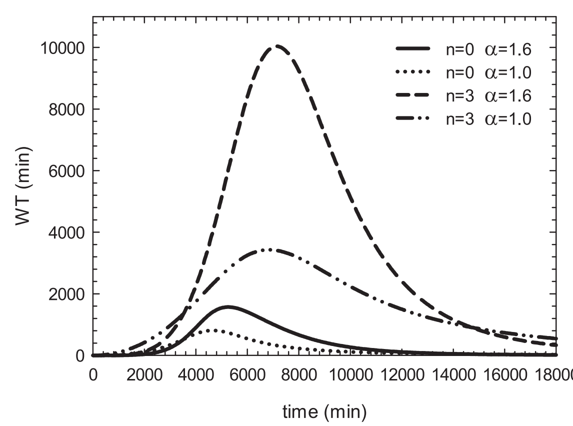

Figure 13. Patient waiting time for the yellow code assuming different numbers of shut down emergency rooms and for different patient arrival rates.

in the previous paragraph is possible to obtain the functionality Q of the ED with different damage levels that are shown in Figure 14.

By assuming a control period T_{LC} = 18,000 min, it is possible to evaluate the different resilience R values using equation (1). The resilience values are given in Table 4, where it is shown a good agreement between the experimental results of the DES model and the analytical metamodel with errors around 1%.

Concluding remarks

Strategic buildings such as hospitals have a critical role in our society and this is the reason why they must

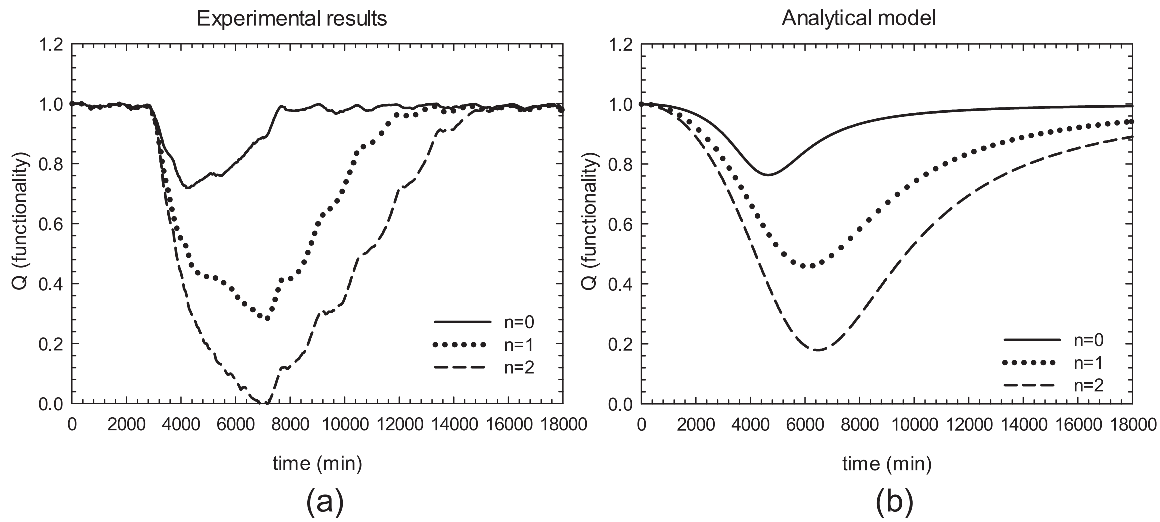

Figure 14. Functionality of the Emergency Department: (a) experimental results using the DES model versus and (b) analytical metamodel.

Table 4. Resilience evaluation for the experimental and the analytical proposed models.

Number of operating rooms not functional	Expt. (%)	Analy. (%)	Error (%)
1	94.68	94.07	0.63
2	78.37	78.00	0.47
3	63.43	64.31	1.38

remain operational during catastrophic events. Therefore, modeling the hospital from the organizational point of view is becoming essential. In literature, several studies are beginning to include also the organizational dimension in their models and are identifying the main parameters which should be used to describe the hospital organizational performance. In this article, the ED of an Italian Hospital has been analyzed while its performance has been measured using an indicator, the patient WT.

The ED has been modeled in detail using a *DES model*, which contains all the *resources* (doctors, nurses, etc.), *locations* (ER, waiting rooms, etc.), *patients*, and so on. Finally, the model has been tested using a seismic wave of patient arrival rates corresponding to an earthquake of given intensity. However, building a comprehensive model such as a *DES model* is time-consuming; therefore, a simplified model called *metamodel* has been developed which takes into account the difference between the patient emergency codes. Different scenarios have been considered which take into account the amplitude of the seismic input and the number of resources available right after the seismic event. Sensitivity of the WT versus the structural damage caused by the earthquake and toward the amplitude of the seismic input has also been investigated. Results show that when an earthquake corresponding to 2% probability of exceedance in 50 year strikes, the average peak patient WT is approximately 13 h. This result is based on the assumption that the incoming patients increase; there is no structural damage; and no application of the emergency plan. Instead, if the assumption of structural damage is released, the average WT increases exponentially by generating the disservice of the ED.

Declaration of Conflicting Interests

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References

Alvanchi A, Lee SH and AbouRizk S (2011) Modeling framework and architecture of hybrid system dynamics and discrete event simulation for construction. *Computer-Aided Civil and Infrastructure Engineering* 26(2): 77–91.

Bhaskar A, Chung E and Dumont AG (2011) Fusing loop detector and probe vehicle data to estimate travel time statistics on signalized urban networks. *Computer-Aided Civil and Infrastructure Engineering* 26(6): 433–450.

Boginski V, Mun IK, Wu Y, et al. (2007) Simulation and analysis of hospital operations and resource utilization using RFID data. In: *Proceedings of the IEEE international conference on components, circuits, devices and systems RFID, 2007*, Grapevine, TX, 26–28 March. pp. 199–204. New York: IEEE.

Boxerman SB (1996) Simulation modeling: a powerful tool for process improvement. *Best Practices and Benchmarking in Healthcare* 1(3): 109–117.

Cimellaro GP and Reinhorn AM (2011) Multidimensional performance limit state for hazard fragility functions. *Journal of Engineering Mechanics: ASCE* 137(1): 47–60.

Cimellaro GP, Fumo C, Reinhorn AM, et al. (2009) *Quantification of disaster resilience of health care facilities*. MCEER technical report-MCEER-09-0009, 14 September. Buffalo, NY: Multidisciplinary Center for Earthquake Engineering Research. Available at: http://mceer.buffalo.edu/publications/catalog/reports/Quantification-of-Disaster-Resilience-of-Health-Care-Facilities-MCEER-09-0009.html

Cimellaro GP, Reinhorn AM and Bruneau M (2010) Framework for analytical quantification of disaster resilience. *Engineering Structures* 32(11): 3639–3649.

Cimellaro GP, Reinhorn AM and Bruneau M (2011) Performance-based metamodel for health care facilities. *Earthquake Engineering & Structural Dynamics* 40: 1197–1217.

Cimellaro GP, Solari D and Bruneau M (2014) Physical infrastructure interdependency and regional resilience index after the 2011 Tohoku earthquake in Japan. *Earthquake Engineering & Structural Dynamics* 43: 1763–1784.

Davies R (2007) "See and Treat" or "See" and "Treat" in an emergency department. In: *Proceedings of the 2007 Winter simulation conference*, Washington, DC, 9–12 December, pp. 1498–1501. New York: IEEE.

Davis DP, Poste JC, Hicks T, et al. (2005) Hospital bed surge capacity in the event of a mass-casualty incident. *Prehospital Disaster Medicine* 20(3): 169–176.

DesHarnais SI, Chesney JD, Wroblewski RT, et al. (1988) The Risk-Adjusted Mortality Index: a new measure of hospital performance. *Medical Care* 26(12): 1129–1148.

DesHarnais SI, McMahon LF Jr, Wroblewski RT, et al. (1990) Measuring hospital performance: the development and validation of risk-adjusted indexes of mortality, readmissions, and complications. *Medical Care* 28(12): 1127–1141.

Hamby L and Fraser S (2004) Using patient waiting-time data to improve the hospital bed-assignment process. *Joint Commission Journal on Quality and Patient Safety* 30: 42–46.

Komashie A and Mousavi A (2005) Modeling emergency departments using discrete event simulation techniques. In: *Proceedings of the 2005 Winter simulation conference*, Orlando, FL, 4 December, pp. 2681–2685. New York: IEEE.

Luo Z and Liu Y (2012) A bi-level model for planning signalized and uninterrupted flow intersections in an evacuation network. *Computer-Aided Civil and Infrastructure Engineering* 27(10): 731–747.

McArthur DL, Peek-Asa C and Kraus JF (2000) Injury hospitalizations before and after the 1994 Northridge, California earthquake. *The American Journal of Emergency Medicine* 18(4): 361–366.

McGuire F (1994) Using simulation to reduce length of stay in emergency departments. In: *Proceedings of the 1994 Winter simulation conference*, Orlando, FL, pp. 861–867. New York: IEEE.

Martin E, Grønhaug R and Haugene K (2003) Proposals to reduce over-crowding, lengthy stays and improve patient care: study of the geriatric department in Norway's largest hospital. In: *Proceedings of the 2003 Winter simulation conference*, New Orleans, LA, 7–10 December, pp. 1876–1881. New York: IEEE.

Nejat A and Damnjanovic I (2012) Agent-based modeling of behavioral housing recovery following disasters. *Computer-Aided Civil and Infrastructure Engineering* 27(10): 748–763.

NTC-08 (2008) *Nuove Norme Tecniche per le Costruzioni*. Consiglio Superiore dei Lavori Pubblici, Ministero delle Infrastrutture [Superior Council of Public Works, Ministry of Infrastructure], Gazzetta Ufficiale della Repubblica Italiana, NTC08, 4 febbraio, n. 29 (in Italian).

Peek-Asa C, Kraus JF, Bourque LB, et al. (1998) Fatal and hospitalized Injuries resulting from the 1994 Northridge earthquake. *International Journal of Epidemiology* 27(3): 459–465.

Pidd M (2003) *Tools for Thinking: Modelling in Management Science*. 2nd ed. Chichester: Wiley.

Price RN (1999) *ProModel Manufacturing Simulation Software: Reference Guide*, version 4.2. Orem, UT: ProModel Corporation.

Samaha S, Wendy AS and Darrell S (2003) The use of simulation to reduce the length of stay in an emergency department. In: *Proceedings of the 2003 Winter simulation conference*, New Orleans, LA, 7–10 December, pp. 1876–1881. New York: IEEE.

Stratton SJ, Hastings VP, Isbell D, et al. (1996) The 1994 Northridge earthquake disaster response: the local emergency medical services agency experience. *Prehospital and Disaster Medicine* 11(3): 172–179.

Takakuwa S and Hiroko S (2004) Functional analysis for operating emergency department of a general hospital. In: *Proceedings of the 2004 Winter simulation conference*, Washington, DC, 5–8 December, pp. 2003–2010. New York: IEEE.

Van der Meer RB, Rymaszewski LA, Findlay H, et al. (2005) Using OR to support the development of an integrated musculo-skeletal service. *Journal of the Operational Research Society* 56(2): 162–172.

Yi P (2005) *Real-time generic hospital capacity estimation under emergency situations*. PhD Dissertation, Department of Industrial Engineering, The State University of New York at Buffalo, Buffalo, NY.