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ORGANIZATIONAL MODEL OF AN EMERGENCY DEPARTMENT UNDER SEISMIC EVENT

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ABSTRACT

The paper presents a hospital testbed which aims to help the earthquake engineering community moving another step toward the realization and implementation of resilience-based design strategies for health care facilities. An organizational model describing the response of the Hospital Emergency Department (ED) has been implemented using a discrete events simulation model (DES). The waiting time is the main response parameter used to evaluate the resilience index of healthcare facilities during earthquakes. A metamodel has been developed from the DES 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 corresponding to 2% probability of exceedance in 50 year strikes, generating a seismic wave of injured patients going to the ED, the average peak patient waiting time is around 13 hours when an emergency plan is not applied, regardless the type of code considered. If the ED is damaged and emergency rooms are not functional the average waiting time can increase dramatically and the ED is not able to provide the proper service.

INTRODUCTION

Healthcare facilities have been recognized as strategic buildings in hazardous events and they play a key role in the disaster rescues. During a dramatic event, the Emergency Department (ED) has a critical role in the health care facilities, as it must provide immediate assistance. Even if EDs are properly organized, a change in the external environment, such as a natural disaster can modify patients' arrival rates and lead to a change in their performance that could end up with a worse service level for all the patients (Davis et al., 2005). This kind of "patients' satisfaction" can be measured with different parameters; among these parameters, the most representative one is the waiting time (Hamby and Fraser, 2004), which gives also an idea of how busy a hospital is. This parameter can be used to measure the response and the capacity of the hospital during emergency (Cimellaro et al., 2011). The goal of the paper is simulating the Emergency Department using a complex Discrete event model and then simplifying the model developing what is called "*metamodel"* using a reduced number of parameters which provides as output the waiting time associated to a given disaster. Then these scenarios are analyzed to consider the effects of the response of the ED to the damage caused by the earthquake and the sensitivity to the amplitude of the seismic input.

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STATE-OF-ART

Several studies for the health care systems have been performed in the recent years, in particular related to the patients' waiting time (Hamby et al., 2004). In fact, the study of multiple patient routings and flow processes is important to reduce the waiting time at various stages in the hospital. This was generally made using simulation models which analyze various scenarios with different performance indicators (DesHarnais et al., 1988, 1990). Models are used in problem solving because their use is generally cheaper, faster and less disruptive than manipulating the real world system (Boxerman, 1996). In particular, discrete event simulation (DES) has been widely used in modeling healthcare systems since the 1970's. Martin, Grønhaug and Haugene (2003) studied the elder patients' admission into a Geriatric Department and different scenarios to reduce the waiting time. Van der Meer at al. (2005) analyzed a case study with the goal of reducing elective patients' waiting times for the Department of Orthopedics. Although only for a single specialty, they found DES models to be a good communication tool between hospital administration and modelers. However, attempts to model whole hospitals are rare. This is because of the difficulty to represent the complexity of hospital activity within a simulation model that must be a simplification (Pidd, 2003). Appropriate simplification can be a complex process, and it may be easier to segment off a discrete part of the hospital, such as a single ward. In this context, Emergency Departments are one of the most popular areas for DES modeling because they are relatively self-contained with easily observable processes. McGuire (1994) discussed the use of DES models to compare different alternatives for selecting a method to reduce the hospitalization of patients. The same goal was followed later by Samaha, Wendy, and Darrell (2003). Takakuwa and Hiroko (2004) constructed a simulation model of the ED to examine patients' flow and waiting times. The reduction of patients' waiting time 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 that generally causes an increase of the waiting time. In this paper, the ED of a hospital has been studied considering the amplitude of the arrival rate due to a seismic disaster and the effect of structural damage of specific parts of the building. Equations have been proposed in order to obtain the waiting time of the patients without need to run the model several times.

A NEW METHODOLOGY FOR EVALUATING RESILIENCE OF HEALTH CARE FACILITIES

The term resilience is used as the capacity of engineering and socio-economic systems to rebound after a severe disaster such as an earthquake (Cimellaro et al., 2010a-b). The most general resilience framework must consider both technical and organizational dimensions, which are interdependent (Cimellaro et al., 2014a-b), each other. In this paper, attention is given mainly to the organizational dimension of resilience for an ED, evaluated by means of a response variable. Based on this assumption, it is observed that resilience has an inverse trend with respect to the waiting time, so if resilience increases, the waiting time decreases.

DESCRIPTION OF THE HOSPITAL

The hospital analyzed in this paper is located in Turin, Italy. The hospital is almost 3 km far from the city center and it contains 17 units which represent different wards. It was built in 1881 but several buildings were added during the twentieth-century and nowadays it covers an overall surface of 52827 m^2. In this study, only the Emergency Department which is located in the building 17 was modeled. As in the other Italian emergency departments, all patients who entered are divided in four different colour 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 in immediate danger of life. Yellow codes (urgency) have a partial impairment but there is not an immediate danger of life. Green codes (minor urgency) have lesions that do not affect vital functions while White codes (no urgency) are all patients who don't really need to be in the emergency department. As consequence of this classification, the ED itself is divided in three main areas. An emergency area is located immediately in front, where the ambulance stops and contains two rooms in which red codes are stabilized. Parallel to this area, there is the yellow and green codes' area composed of five emergency rooms. White codes are seen in their own emergency room, during its working hours; otherwise, they have to wait until yellow and green patients' emergency rooms are available. Inside the emergency department, there are also recovery rooms in which patients can stay before being discharged or recovered in another part of the hospital (Figure 1).

DISCRETE EVENTS SIMULATION MODEL

For the simulation of the hospital operations, a discrete event simulation (DES) model is used (Figure 1). The model is implemented using a commercial software called Promodel (Price, 1999) by defining the parameters needed as the patients' arrivals, the paths through the ED, the different rooms where patients could be attended, the processing times and the procedures that take place in each location, as well as all the resources such as nurses or doctors. All these parameters are simulated in a DES model which is represented in Figure 1, in which the different emergency rooms, paths, counters for the number of patients, patients and hospital personnel are shown.

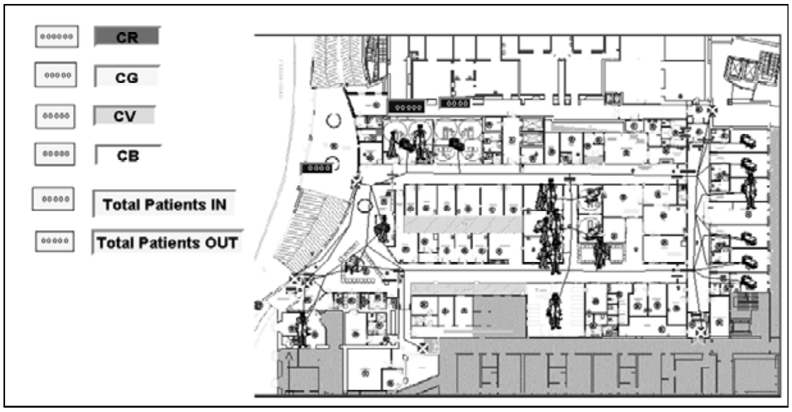


Figure 1. DES model of the Emergency Department, extract from Promodel software (1999).

For the study of the ED, some assumptions of the DES model are done to simplify the study. The model has been analyzed using the patient arrival rate both in normal and emergency operating conditions right after the seismic event. In this phase the main assumption is that the hospital structural and non-structural parts remain undamaged, so the difference between the normal operating conditions and the emergency operating conditions consists in a different patients' arrival rate. Moreover, it is assumed that, even after a dramatic event strikes, the system behaviour remains the same with respect to the normal operating conditions. This is an unrealistic assumption because, in dramatic conditions, many characteristics of the system change, but these modifications have not been 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. As explained in the previous paragraph, the arrival rates 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 change occurs in the same point for all the codes during the analysis.

INPUT DATA ANALYSIS

The first step for developing the simulation model is to collect all necessary data involved in the modelling. The data needed for the simulations are the ED flow charts, the procedures inside the different rooms, as well as the personnel (known as resources) needed for each action and the patients' arrival rate to the ED. As mentioned before, there are four different codes arriving to the ED and, for this reason, four different arrival rates of patients (Yi, 2005) were calculated for the simulation, by using, the hospital's register statistics. Figure 2 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 injury codes and in weekdays and weekend.

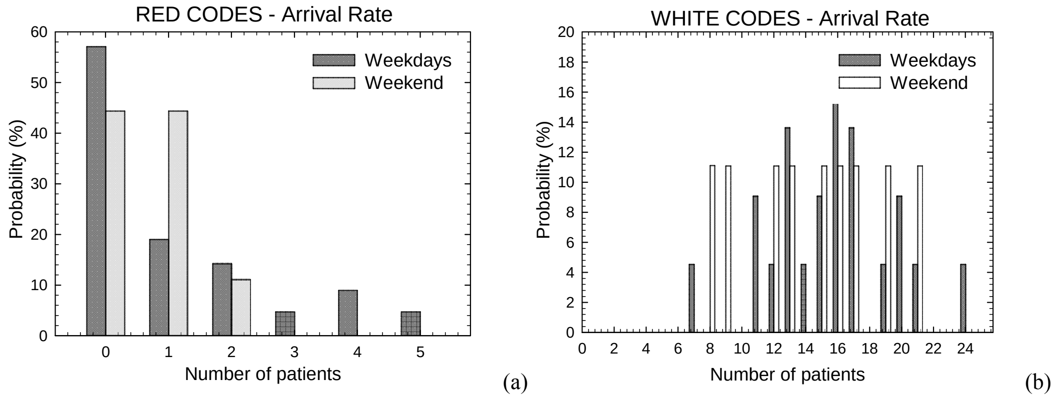


Figure 2 Probability of occurrence of patients' arrival rates divided into weekdays and weekend for (a) red code patients, (b) white code patients.

The distribution of the patients' arrivals in a day is defined by the arrival cycle (Figure 3) which represents the percentage of daily patients that arrive at a given instant of the day. The data were extracted by the hospital registers.

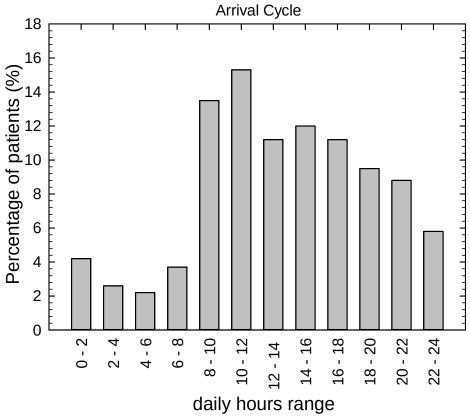


Figure 3. Patient daily arrival cycle.

The patients' flow chart was determined both by interviews with personnel and statistical data provided by them. The different paths that a patient could follow after entering in each room are determined. Then, by analyzing the hospital statistics, the percentage of patients following each path is determined as well as the percentage of patients that changes their injury code because of an improvement or an aggravation of their injury. The resources involved in each process as well as the time table of the personnel are also used. The resources employed and simulated in the ED are 7 doctors, 9 nurses, 4 assistants and 2 health workers.

PATIENT ARRIVAL RATE SEISMIC INPUT

First, the arrival rate in a Californian hospital during Northridge earthquake was selected and scaled using the PGA corresponding to the Mauriziano hospital located in Turin (Figure 4). However, the scaling procedure based on the PGA has some limitations, because it doesn't take into account the real level of damage related to the area and the population density in which the earthquake happens.

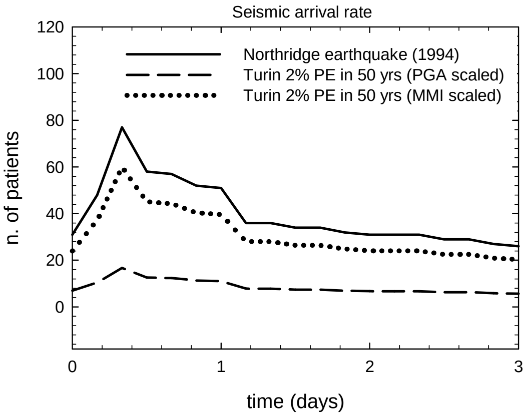


Figure 4. Arrival rates for Northridge earthquake and arrival rate scaled with respect to PGA and MMI.

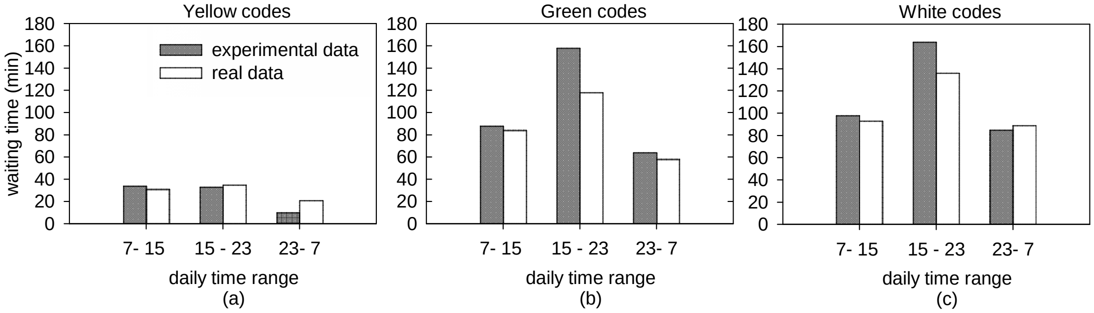
Therefore a second scaling procedure based on the Modified Mercalli Intensity (MMI) scale was selected. The seismic arrival rate was then divided in different colour codes following a similar distribution proposed by Yi (2005) shown in Table 1.

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%	3.7%	21
Yellow	16.78%	40.10%	271
Green	71.19%	48.48%	224
White	11.47%	7.81%	43

DATA ANALYSIS

The parameter that has been used to calibrate the model is the waiting time (WT) which is the time the patients spend in the waiting rooms 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 5).



(a)
(b)
(c)

Figure 5. Comparison of real vs. experimental simulated data for (a) yellow codes; (b) green codes and (c) white codes.

After calibration, Monte Carlo simulations were run by performing the thirteen days simulation multiple times. In this way, the random differences between multiple runs are taken into account. The average waiting time is plotted in Figure 6, for yellow, green and white codes respectively. As can be observed, the waiting time increases when the earthquake strikes and goes back to the initial value after the three days of emergency period.

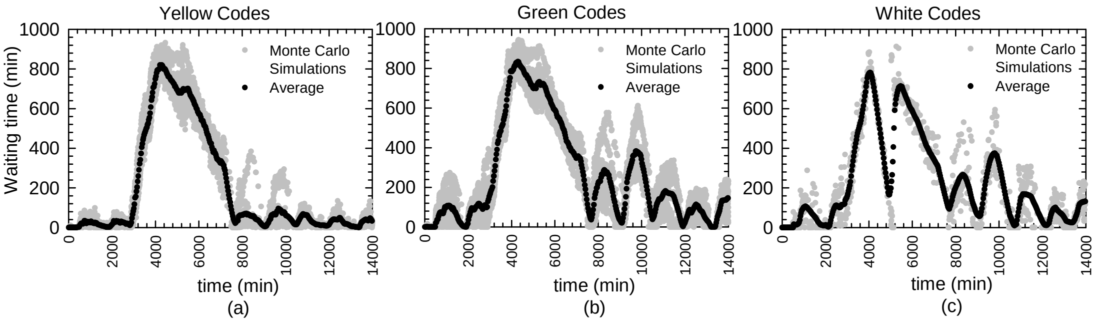


Figure 6. Waiting time for (a) yellow codes; (b) green codes and (c) white codes, under seismic input.

METAMODEL

The Discrete event simulation model (DES) that has been built is a simplification of real-world system and gives an idea of how a complex system such as the Emergency Department is. However, often is necessary to model not a single hospital, but a network of hospitals to perform simulation at regional level. In this case using DES models to run multiple analyses on multiple hospitals to estimate the network capacity is computationally expensive. For these reasons, there is need to create a simpler model, called *metamodel*, whose purpose is describing the system behavior by means of few response variables. 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 emergency rooms etc. The current research is proposing a metamodel which can distinguish between the various colour codes, improving previous existing models (Cimellaro et. al., 2011; Yi, 2005), which are based on a single type of patient for the ED. The main output parameter is the waiting time (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 not functional emergency rooms. Finally two equations for the emergency Department have been proposed which have been determined using curve fitting procedures.

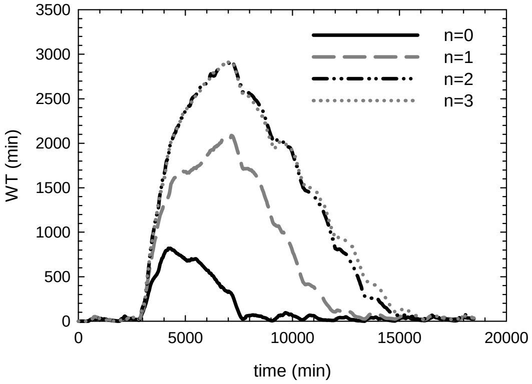


Figure 7. Waiting time of the yellow code in the DES model for different damage states where n is the number of not functional emergency rooms.

The Emergency plan is not taken in account in the current model, but it will be the object of future research. First sensitivity analysis has been performed by simulating the closure of emergency rooms (ER) one by one (n), assuming structural damage in the ER which makes it not functional. The increments of the WT for the yellow codes due to the closure of n emergency rooms are shown in Figure 7. Figure 7 shows that by closing the emergency rooms the WT increases and in particular for n=2 and n=3, the waiting time curves are very close. The reason of this behavior can be explained by the fact that one of the emergency rooms only works some hours a day during weekdays and it is closed all day during the weekend, so using this emergency room or not doesn't considerably affect the yellow codes patients waiting times.

After fitting different equations to the data shown in Figure 7, the following equation has been selected

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

with

$$a(n)=\frac{1}{-444.55522-3725.6162n} \tag{2}$$

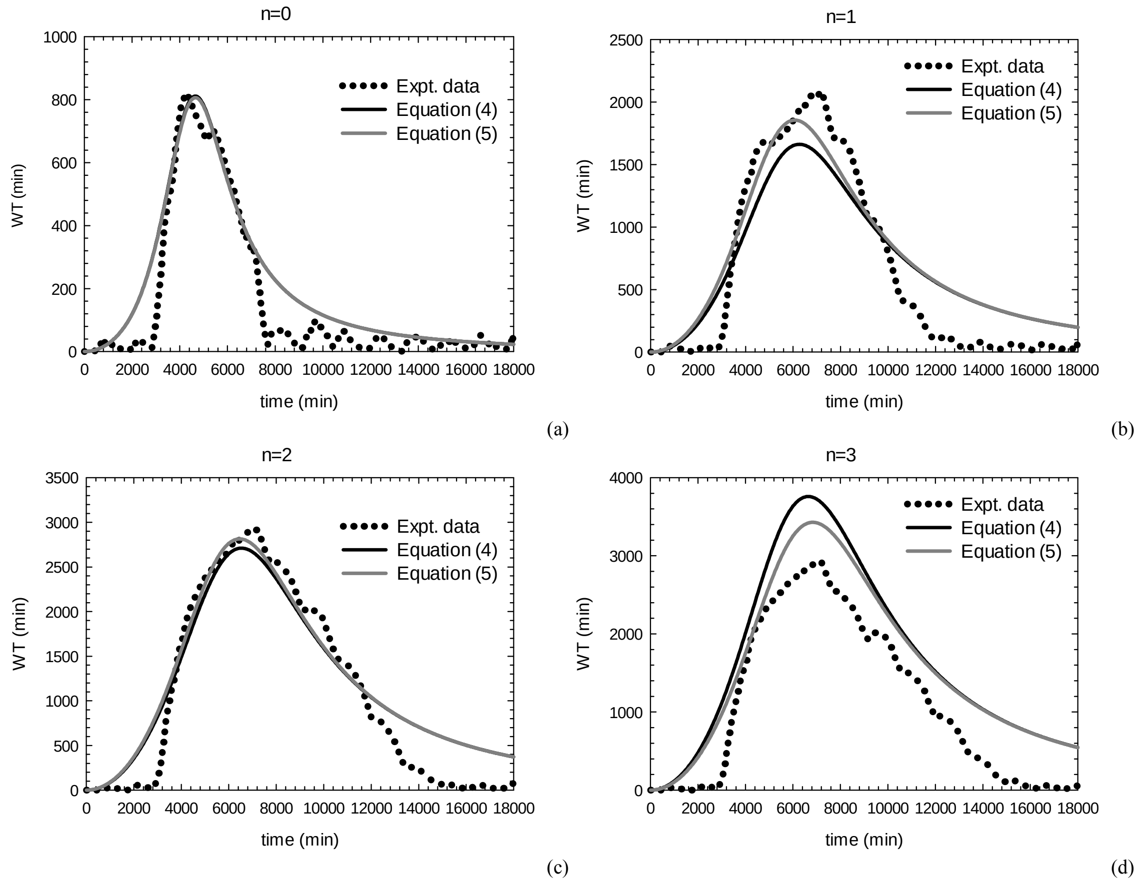
$$b(n)=\frac{1}{9.5429351\cdot 10^{11}+7.354141\cdot 10^{12}n} \tag{3}$$

$$c(n)=\frac{1}{2.3885795\cdot 10^{-5}+3.0610773\cdot 10^{-5}n} \tag{4}$$

where *WT(t, n)* is the waiting time in minutes, *t* the time in minutes and *n* the number of not functional emergency rooms. The comparison between the numerical results and the analytical model is shown in Figure 8. By observing Figure 8, the model in Equation (1) using the parameter *c(n)* in Equation (4) has a good fitting for all the *n* values except for *n=3*. As aforementioned (Figure 7), for the value of *n=2* and *n=3*, the waiting time curves for the experimental data are very similar. When doing the fitting for the parameter c(n) in Equation (4), 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 this discrepancies:

$$c(n)=e^{9.1144666+1.5318346\cdot e^{-n}} \tag{5}$$

The results of the model in Equation (1) using the parameter *c(n)* in Equation (54) are shown also in Figure 8. The comparison of the waiting time *WT(t ,n)* for both equations shows that equation (5) fits better for *n=1* and *n=2*, even though for *n=3* there are still some divergences between simulated values and analytical model.



(a) (b) (c) (d)

Figure 8. Experimental data vs Equation (1) using the parameter c(c) in Equation (4) and (5), for (a) n=0, (b) n=1, (c) n=2, (d) n=3

SENSITIVITY OF THE WAITING TIME TO THE SEISMIC INPUT

In this paragraph is investigated the effect of the seismic input on the waiting time performing a sensitivity analysis. The seismic arrival rate has been amplified proportionally performing a sort of Incremental Dynamic Analysis (IDA) using the seismic arrival rate given in Figure 4. The scaling factors adopted for the analysis are listed in Table 2. Montecarlo simulations has been performed and the average WT for each scaling factor has been considered as target for the analytical model used to fit the experimental results.

Table 2 r^2 values of equation (8) 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

The proposed analytical model is the following

$$WT(t,n) = \frac{1}{d(\alpha) + e(\alpha)t^{2.5} + \dfrac{f(\alpha)}{t^2}} \tag{6}$$

with

$$d(\alpha) = \frac{1}{\dfrac{-130662.61}{\alpha} + 354373.19 \cdot e^{-\alpha}} \tag{7}$$

$$e(\alpha) = \frac{1}{\dfrac{2.8903288 \cdot 10^{14}}{\alpha} - 7.8398432 \cdot 10^{14} \cdot e^{-\alpha}} \tag{8}$$

$$f(\alpha) = e^{8.9580246 \ln \alpha + \frac{10.938463}{\alpha^{1.5}}} \tag{9}$$

Equation (6), with its 90% confidence interval bound, and the residuals plots for the scales factors α=1.1 and α=1.6 are shown in Figure 9. The r^2 values of Equation (6) for the different scaling factors of the seismic input show good agreement with the experimental data as shown in Table 2.

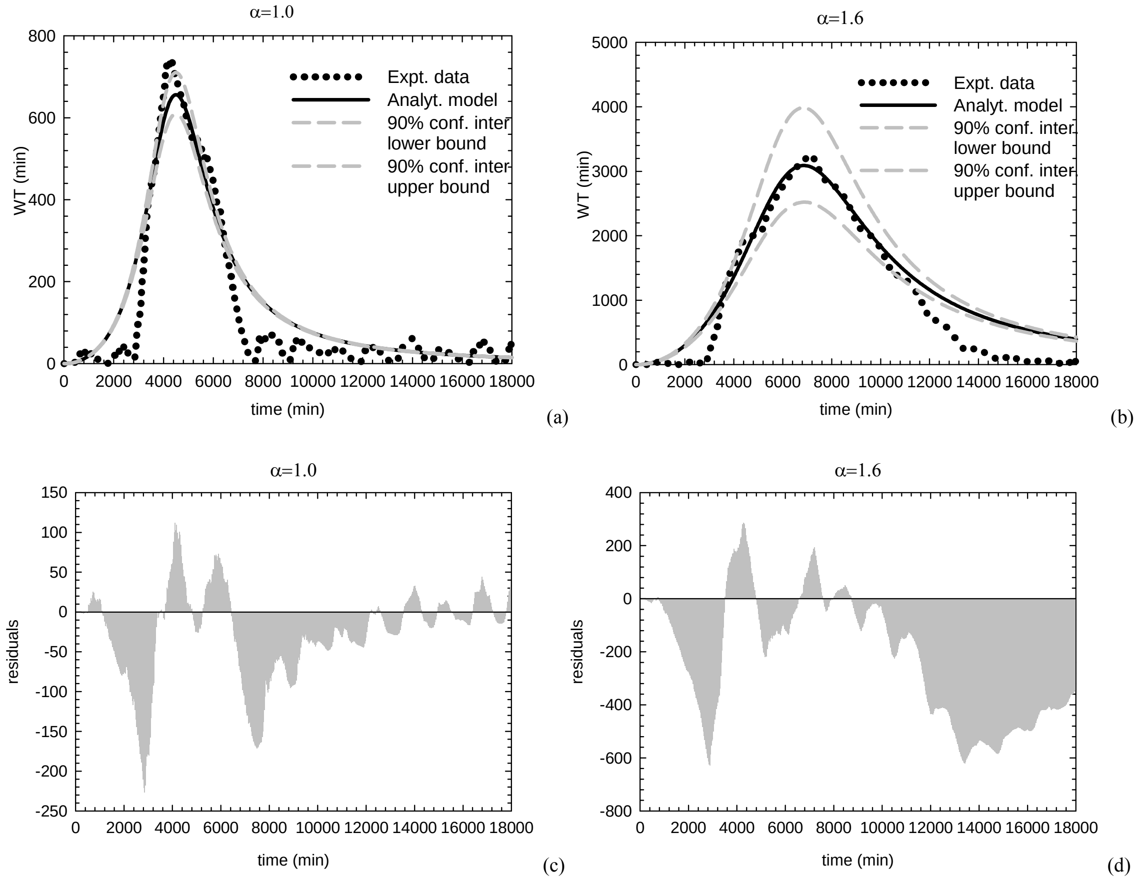


Figure 9. Experimental data vs analytical model for (a) α=1.0; (b) α=1.6 (c-d) residual plots.

Finally the analytical WT model given in Equation (6) is shown in Figure 10 for the different amplification factors of the seismic input.

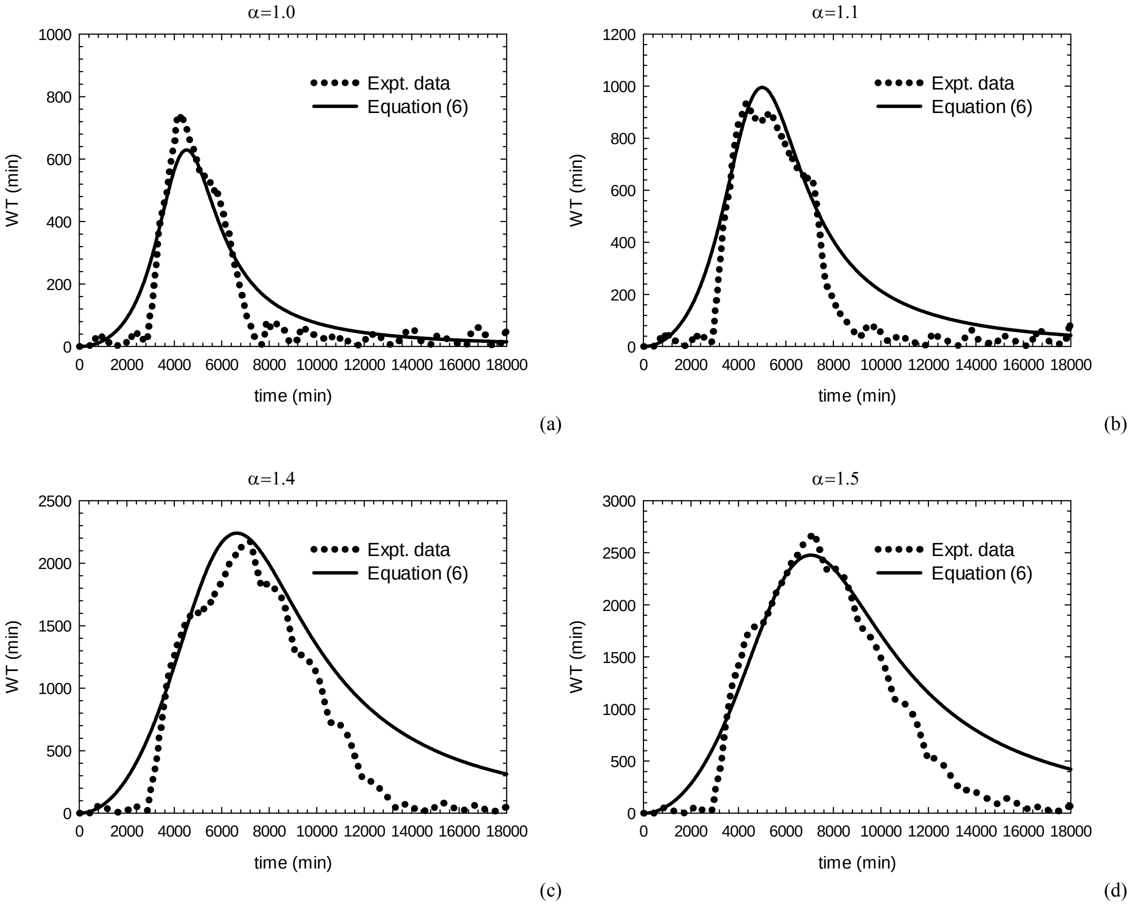


Figure 10. Experimental data vs equation (6), for (a) α=1.0; (b) α=1.1; (c) α=1.4; (d) α=1.5

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.

Table 3 Error between the experimental and analytical model in Equation (6) 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	20.55%

The highest error at the peak is20.55% obtained for α=1.6, but in general the proposed metamodel show good agreement with the experimental results.

CONCLUDING REMARKS

Strategic buildings such as hospitals have a critical role in our society and this is the reason why they must remain operational during catastrophic events. Therefore, modeling the organizational part of the hospital is becoming more and more important. Few studies available in literature are also starting including the organizational dimension in their model, and are identifying the main parameters which should be used to describe the hospital organizational performance. In the current work, the patients' waiting time (WT) is the main parameter that has been used to identify the performance of the ED. As case study, the ED of an Italian Hospital has been considered. An organizational DES model has been built, which contains all the resources (doctors, nurses, etc.), locations (emergency room, waiting rooms, etc.), patients which are needed to have a very detailed model of the ED. Finally the model has been tested using a patient arrival rate corresponding to an earthquake of given intensity.

However, building a comprehensive model such as a discrete event simulation model is time consuming; therefore, a simplified model called metamodel has been developed which takes in account the difference between the patient emergency codes. Different scenarios have been considered which take in account the amplitude of the seismic input and the number of resources available right after the seismic event. Sensitivity of the waiting time vs. the structural damage caused by the earthquake and towards 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, generating a seismic wave of injured patients going to the ED, the average peak patient waiting time is approximately 13 hours when an emergency plan is not applied, regardless the type of code considered. If the ED is damaged and emergency rooms are not functional the average waiting time can increase dramatically and the ED is not able to provide the proper service.

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