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Abstract

Understanding human behavior and predicting evacuation processes subsequently to an earthquake are critical aspects to provide valuable information to support disaster response activities. One possible and relevant aspect that characterizes human behavior in emergency situations is panic reactions, which can lead to dysfunctional and irrational responses by fugitives. Given the relevance of this component, this paper implements a panic behavior model in a large-scale agent-based model considering phenomenal parameters, such as seismic damage to the built environment, disruption of roads by earthquake-induced falling debris, and injuries of individuals. The proposed model is applied and tested in IdealCity, a virtual city simulation environment which resembles the geometry of the city of Turin, with about 900,000 inhabitants. The numerical simulations show that the inclusion of a panic behavior model increases the evacuation time despite the increased speed of agents during the evacuation process and this is probably caused by the fact that pedestrians tend to perform random actions before reaching their destination. Furthermore, existing human relationships between agents tend to convert the crowd from individual agents to group of agents that move together, and this behavior might affect the shelter saturation time of both shelters and hospitals as shown in the simulations analyzed in this paper.

Keywords: large-scale, earthquake, agent-based, human behavior, evacuation.

1 Introduction

Many unexpected disasters, such as hurricanes, earthquakes, floods, and landslides, have impacted on communities in recent years. As urbanization increases, the complexity of infrastructures (e.g., buildings, transportation, and distribution networks) and their interconnections also continues to grow. Researchers are primarily interested in simulating and evaluating the population's response in emergency evacuation situations to improve evacuation strategies, minimize evacuation time, and decrease the number of casualties and injuries (Mikulik et al. 2014; Meng & Jia 2017; Wang et al. 2020). Current crown simulation approaches can be divided into three categories: *flow-based, entity-based, and agent-based* (Qiu & Hu 2010; Zhou et al. 2010). The first one neglects individual characteristics in large-size crowds as it treats the crowd. The second method builds crowd simulations without taking individual behavior into account. Finally, *agent-based models* (ABMs) represent the individuals as agents and define their behaviors and characteristics through a set of rules associated with each agent type (Bonabeau 2002). Recently, ABMs have been frequently applied to quantify community resilience to natural and human-caused disasters (Solís & Gazmuri 2017). ABMs allow a computational description at the level of analysis of agents, interactions of the agents, and they can help to verify the agents' behaviors (Squazzoni 2014). For instance, Kang et al. (2022) proposed an ABM to simulate stochastic occupant movement in buildings by using Immersive Virtual Environments (IVEs). Bina & Moghadas (2021) applied a BIM software with the human behavior simulation engine (AnyLogic code) upon the ABM to simulate emergency evacuation from a conference hall. A novel ABM that incorporates the social dimension of group loyalty into fire evacuation was proposed by Young & Aguirre (2021). Bernardini et al. (2021) tried to analyzed how the pedestrian evacuation behaviors can affect the emergency strategies. Lumbroso & Davison (2018) described the use of an ABM to evaluate the effectiveness of emergency management interventions accounting for the physical parameters of the agents. Sreejith & Sinimole (2022) studied the pedestrian evacuation process by considering the demographic, geographical, and behavioral aspects.

Lei et al. (2012) described an ABM to analyze the effects of evacuation density and exit width on evacuation time. An ABM was developed by DiCarlo & Berglund (2021), who simulated the behavior of a community in using social media network for requesting help during a hurricane.

Although these models describe the simulation of the evacuation behavior, they lack the analysis of the effect of panic behavior, which can affect the evacuation route and the evacuation process speed during emergency evacuation (Zhou et al. 2018; Cimellaro et al. 2019; Melo et al. 2020).

Recently, a limited number of studies available in the literature include panic behavior in ABMs. Hassanpour & Rassafi (2021) introduced a prototype of ABM using the affordance concept to simulate the decision-making process during an emergency evacuation. The approach was tested to model the behavior of agents in a subway through normal and emergency condition. Abu Bakar et al. (2016) designed a dynamic ABM to simulate the panic behavior models during stressful events.

In this context, most of the research available in the literature focuses on small-scale scenarios such as building evacuation (Tang & Ren 2008; Lin et al. 2010; Xiao et al. 2016; Kasereka et al. 2018; Poulos et al. 2018). When it comes to large-scale emergency evacuation, complex interactions between individuals exhibiting nonlinear and irrational behaviors should be considered (Helbing et al. 2000a). To the best of knowledge, panic models in large-scale emergency scenario have been largely unexplored in the literature (Song et al. 2014). Therefore, the innovative contribution of this research consists in the insertion of a human behavior model within a multi-layer large-scale evacuation ABM, that has been presented in previous work (Battegazzorre et al. (2021). In addition to the panic behavior of individual agents, the human group behavior to reproduce social collective actions of individuals has been also included in the proposed model. The proposed agent-based approach is presented to assist decision-makers in evaluating critical response parameters at the community level and in analyzing the impact of panic behavior and the group behavior on the evacuation process at the large simulation scale, along with the emergency response of critical facilities at the local scale. The paper sections are structured as follows: Section 2 describes the emergency evacuation model with reference to the relevant prior literature. Section 3 presents the human behavior model adopted in this work. Section 4 describes the implementation of the IdealCity hybrid model along with the seismic scenarios adopted for the emergency evacuation simulations. Section 5 presents and discuss the results of the simulations. Finally, conclusions are drawn in Section 6 together with the proposed future work.

2 Emergency evacuation modeling

2.1 Ideal City

IdealCity is a hybrid model that can be adopted as a general framework to simulate cities with different features such as building categories, infrastructure systems, and their interdependencies. The virtual city includes the Socio-Technical Network (STN) response (e.g., emergency rescue and evacuation), which is composed of an ABM capable of managing the entire city population. The city model used in this work reflects the characteristics, such as road transportation network, building type, year of construction, height classifications, and occupation of the town of Turin in Italy. The urban area of Turin is about 130 km^2 and the city has more than 900,000 inhabitants. Further information can be found in Marasco et al. (2020); Battegazzorre et al. (2021). The ABM has two types of agents: *individuals* living in IdealCity and *ambulances* that are supposed to rescue severely injured people and transport them to hospitals (Battegazzorre et al. 2021). Other included systems are the *city buildings, shelters,* and *hospitals*. Shelters and hospitals have a certain and well-defined capacity; beyond which they cannot accept new agents. Each person in indoor environments has a health condition: *healthy, lightly injured* (the ability to walk is maintained), *severely injured* (the agent can't move autonomously and requires the assistance of an ambulance), or *dead*. The outdoor agents, on the other hand, are randomly positioned along IdealCity, and their health condition is determined by their proximity to the rubble of the damaged buildings.

2.2 Damage of buildings

Seismic events can cause severe damages to existing structures reducing their functionality for a certain recovering period. Quantifying such damages can help with not only evacuation modeling, but also seismic risk evaluation, emergency management planning, and loss prevention (De Iuliis et al. 2019).

An innovative surrogate model capable of representing the response of thousands of multi-story buildings in the virtual city named as IdealCity is employed to reduce the computational efforts. Indeed, the surrogate model allows the number of degrees of freedom of seismic analysis to be drastically limited, without decreasing the degree of seismic response prediction (Domaneschi et al. 2018; Marasco et al. 2021). The surrogate model predicts the expected per-building damage level (from none to complete (HAZUS 2015)), the amount of debris produced and to what extent this may affect the availability and efficiency of the urban transportation network.

The suggested surrogated model is a Single Degree Of Freedom (SDOF) system able to approximately reproduce the building behavior. A backbone curve representing the seismic capacity of the whole individual structure, with the hysteresis behavior under cyclic loading and shear strength degradation as well, is determined for each building (Domaneschi et al. 2018; Marasco et al. 2020).

A Machine Learning (ML) approach is implemented to estimate the debris generation and extension (Mitchell 1997; Bishop 2006; Goodfellow et al. 2016). The debris extension is computed for each image using photogrammetric algorithms that utilize the dimensions of recognized objects. Then, normalized parameters (debris size over the structural dimensions) and different metadata are adopted to process the database. Finally, the inference engine uses these metadata to forecast the debris extensions of unseen structures for a given earthquake. Several approaches to predicting accuracy in terms of R^2 and Mean Absolute Relative Distance (MARD) are investigated. R^2, also known as coefficient of correlation, is the square of the sample correlation coefficient between the predicted values and the ground truth. MARD is the average vertical distance between each point and the regression line computed by the ML algorithm. As a result, the lower the MARD, the more precise the prediction.

The classifiers are trained using K-fold Cross-Validation, with 80 percent of the images in the training set and the remaining samples were divided equally between test and validation tests. Table 1 reports the R^2 and MARD values for the analyzed ML algorithms. Results show that Random Forest (RF) and k-Nearest Neighbors (k-NN) are the best performers. That is, k-NN has the lowest MARD (0.32), yet a low value of R^2 (0.42). On the other hand, RF achieves the best R^2 (0.62) and a satisfactory MARD value (0.56). Therefore, RF is chosen as the classifier to use in the model.

Table 1. R^2 and MARD scores for ML algorithms

Algorithm	R^2	MARD
Random Forest (RF)	**0.61**	0.56
k-Nearest Neighbors (k-NN)	0.42	**0.32**
Lasso	0.54	0.53
Elastic Net	0.54	0.53
Ridge	0.54	0.52
Decision Tree	0.56	0.60
SVR	0.43	0.53
MLP Regressor	0.49	0.53

3 Human behavior modeling

Developing a realistic simulation model requires a thorough understanding of human behavior during emergencies. However, accurately formulating the behaviors of agents and their decision-making mechanisms in emergencies is challenging because they are influenced by many factors. For example, in an earthquake, the debris may not only impede evacuation routes but also affect the number of options and actions available. Nevertheless, this is a relevant feature of any simulation model, as deaths and injuries can be due to the emergency event, but also to human factors such as panic and irrational behaviors (Cocking & Drury 2008).

In general, panic behavior can be analyzed at different levels (Pan et al. 2007). At the micro-level, individual behavior is influenced by physical and mental factors. Physical parameters include age, gender, current location and speed, and health status. Mental factors include knowledge about the environment, agent's emotions (e.g., sadness, fear, anger), agent's experience, and so on. At the macro-level, an agent's decision-making process is influenced by three main factors: instinct, experience, and bounded rationality (Pan et al. 2007; Şahin et al. 2019). The simplest way to respond to an event in an emergency is instinct because it does not require the involvement of the conscious component of intellect. Moreover, two factors can increase individuals' panic and stress levels, and reduce their ability to make rational decisions: namely crowd density and environmental constraints, e.g. the presence of stairs or doorways in indoor environments (Pan et al. 2007).

Focusing on the group behavior modeling, the interactions between individuals in the group can be either cooperative or competitive. For example, an individual may decide to follow a leader who shows greater leadership qualities or to isolate herself to avoid collisions with others (Sharma et al. 2016). Under these conditions, it is also necessary to consider the cohesion between group members, which is certainly stronger in the case of friendship or family relationships that lead to the creation of micro-groups, often with two to four members. This cohesion persists even in emergencies and group members tend to stay together rather than flee alone (Drury et al. 2009). Furthermore, it has been found that individuals within a cohesive group are more likely to make evacuation choices that are better for the group as a whole (Sime 1983).

Another element to take into consideration is that panic in emergencies leads to collective behaviors in which judgment and reasoning are impaired, and strong feelings of anxiety arise, leading to irrational behaviors, which can result in self and hetero-destructive actions (Helbing et al. 2000a; Helbing et al. 2000b). In addition, people tend to move faster than their desired level of speed (Predtetschenski & Milinski 1971). Another common effect in panic situations is that the evacuation process is slowed down by injured and panicked people who become “obstacles.” In these cases, alternative exits are often overlooked in emergencies (Elliott & Smith 1993), even though people in normal visibility and without panic are able to find an exit by the shortest route. As a result, evacuation of a person affected by panic is much less efficient and can take a long time, as people tend to move in the direction where they expect to find safety. However, their movement is irrational as long as they are panicked (Helbing & Johansson 2013).

3.1 Agent behavior

To better represent a crowd behavior simulation for large-scale systems with many components, a multi-agent system is implemented in this work. Each dweller is represented as an autonomous agent with a set of attributes, physical and psychological. Physical attributes include position, health status, gender, and age, while psychological attributes include knowledge about the environment, agent's emotions (e.g., sadness, fear, anger), agent's experience, emergency decision making ability, psychological enduring capacity, etc. As in Battegazzorre et al. (2021), the agents' ages and genders are chosen at random based on the population distribution of IdealCity (Capozzo et al. 2019; Battegazzorre et al. 2021).

3.1.1 Panic behavior

The panic possibly affecting agents has been modeled as follows. As soon as an agent is spawned, it is assigned with a *panic level* (*pl*) value between 0 and 1 computed as Equation 1.

$$pl = (a \cdot k_a + b \cdot k_b + c \cdot k_c + d \cdot k_d) \qquad (1)$$

where *a*, *b*, *c,* and *d* are variables with values between [0,1] representing the psychological, physical, and environmental features that contribute to the agent's panic state and the constants k_a, k_b, k_c and k_d are their weighting factors (again in [0,1]).

In detail, *a* is a randomized number that accounts for the agent's *predisposition to panic* (Lu et al. 2019), while *b* is obtained from the mean injury level (*il*) of other individuals in the immediate vicinity of the agent (i.e. in the same building for indoor agents, or within a small radius, defined as a simulation parameter for outdoor agents). Parameter *b* is computed as Equation 2.

$$b = \frac{\sum_{i=1}^{N} il_i}{N} \qquad (2)$$

where N is the number of nearby agents and their injury level il_i assumes discrete values related to the health state of the agent (namely, 0 for healthy agents, 0.33 for lightly injured agents, 0.66 for the heavily injured, and 1 for the dead).

The c parameter reflects the amount of debris that covers and blocks the evacuation path; it depends directly on the average damage level dl of the buildings in which indoor agents are located and in the immediate vicinity of the outdoor agent (according to suitable threshold, e.g., a circular area of radius 25m around the outdoor agent). The formula for c consists in Equation 3.

$$c = \frac{\sum_{i=1}^{M} dl_i}{M} \tag{3}$$

where M is the number of building in the agent's vicinity and each building damage level dl is divided into five tiers, in accordance to (HAZUS 2015), i.e., 0 for undamaged buildings, 0.25 for slight damage, 0.5 for moderate damage, 0.75 for extensive damage, and 1 for destroyed structures.

The last parameter d reflects the agent's own injury level, where d is equal to 0 for uninjured agents, and 1 for lightly injured ones. Heavily injured and dead states are not considered in this formula, since heavily injured agents are unable to move, and dead agents are removed from the simulation altogether; hence their panic state is irrelevant to the simulation unfolding.

These four parameters all undoubtedly contribute to an individual's panic state (Wang et al. 2012; Lu et al. 2019); however, according to current knowledge, it is undetermined *how much* each of these factors influence one's behavior in an emergency evacuation situation. Therefore, in the simulations, it has been assumed that each factor equally contributes to the *panic level* (i.e., the same value 0.25 is assigned to all constants k_a, k_b, k_c and k_d). Furthermore, since specific studies of the four parameters are missing in the literature, the range of each parameter has been preliminary assumed by the authors as linearly increasing. Determining the appropriate value of each of these parameters and the corresponding constants goes beyond the scope of this paper and should be the subject of further study.

Once computed at startup, if an agent's *panic level* is lower than a predefined threshold, the agent is not affected by a panic attack and therefore acts according to the model's rules defined in

(Battegazzorre et al. 2021), where agents try to reach the closest shelters, hospitals, or city exits. Otherwise, if the agent's panic level exceeds the threshold, the agent is considered affected by a panic attack (i.e., he is subject to panic behavior), and behaves accordingly, i.e., it is confused and unable to identify its corrected destination. This is represented in the ABM by the agent moving towards a randomly determined point in the city. By varying the value of the panic threshold, it is possible to modulate the percentage of agents that are affected by panic attacks in the simulation. For example, a low threshold will result in a high number of agents panicking, while a high threshold will decrease their number.

As for the duration of a panic attack, this lasts between 5 and 20 minutes according to (Barlow et al. 1994; Healthwise Staff 2020). Therefore, in the simulations, if a panic attack is triggered, its duration is computed as a function of the panic level pl (Equation 4).

$$panic\ time = 5mins + (pl * 15\ mins) \tag{4}$$

When the panic attach expires, the agent resumes its normal behavior (i.e., tries to reach the nearest shelter or hospital). If the panicked agent reaches its (randomly determined) destination before the panic time expires, another random destination is selected.

Beyond causing an erratic movement behavior, a panic attack causes the agent to increase its speed, as explained in (Barlow et al. 1994). Thus, the walking speed of a panicked agent is calculated as Equation 5.

$$v_a(t) = v_{a0}(1 + pe(t)) \tag{5}$$

where v_{a0} is the agent's walking speed, without considering panic and $pe(t)$ is the panic effect on (i.e., increase in) walking speed at time t due to panic. The walking speed v_{a0} is a function of the amount of debris on the streets (Lu et al. 2019) and the agent's age and degree of injury computed as follows. The initial pedestrian "normal" speed v_{a0} is randomly chosen from a range between a normal (comfort) and a peak (maximum) walking speed depending on age and gender (Bohannon 1997). Then, light injuries affect the agent's walking abilities, reducing v_{a0} by a varying arbitrary percentage between [40% and 80%] (see (Battegazzorre et al. 2021) for details). As for *pe(t)*, its value decreases exponentially over time according to the following Equation 6.

$$pe(t) = \begin{cases} pl * (1 - e^{(-ln2/t)}), & t < panic\ time \\ 0, & t \geq panic\ time \end{cases} \quad (6)$$

3.1.2 Group Behavior

Group behaviors (GBs) are examples of social collective behaviors because they often have social and cultural manifestations. This behavior occurs when some evacuees are faced with uncertainty about what is going on and what they can do to protect themselves and others they care about (Cialdini 1993; Pan 2006). In such a situation, evacuees who are uncertain about which path to take may choose to follow others who appear to be acting more deliberately. Self-organized social systems develop stable patterns of interaction among participants (Parsons & Shils 2017). Mann (1969) pointed out that group cohesion is achieved when informal rules are established that allow individual members to conform to the behavioral pattern of the collective.

Since GB affects emergency evacuations by introducing collective behaviors, it has been included in the model by defining a "group" as a unit of *n* individuals moving coherently toward the same destination and at the same speed. Groups are dynamic in that the number of members can change during the lifetime of the group, as will be explained later. Regarding the formation of groups, groups with high closeness have been first considered (e.g., families and friends), which tend to search for other members of their own group before trying to evacuate. Then, in addition to single agent, the ABM also supports groups with two, three, or four members that are formed, for indoor pedestrians, when agents are spawned from buildings and, for outdoor pedestrians, according to a clustering heuristic that consider a suitable distance threshold. Then, the agent group affinity is considered for the group formation, i.e., the individual willingness of the agent to join a group, which is defined heuristically as exemplified in Section 5.

Once a group is formed, the group behavior is determined according to the following rules:

- the role of “group leader” is assigned to the member with the lowest *panic level*. The *panic level* of the leader determines the panic level of the group and thus, according to the rules described above, whether the group is affected by a panic attack.
- The overall speed of the group is set to that of its slowest member. For example, an elderly or injured person affects the evacuation speed of everyone in the group.

Once these attributes are defined, the group moves towards one of three possible destinations:

1. *Random destination:* if the group leader has succumbed to panic, the group moves erratically as described in the previous section for individual agents.
2. *Shelter:* if not in panic and everyone in the group is uninjured, the group tries to reach the nearest safe shelter. If the shelter is full, members search for another shelter with vacancies or leave the city as individual agents would. (Note: in the borderline case where, for example, a group of four reaches a shelter with only three vacant spots, it has been assumed that shelter operators would be unwilling to divide a family and they are taken in regardless of the currently available places. Technically the maximum capacity of a shelter could be exceeded by a maximum of three individuals, however, this is not a problem since such occurrences can be expected in the chaos of an emergency)
3. *Hospital:* if at least one of the members is lightly injured, the group moves towards the closest hospital. Once a hospital with a vacancy is reached, the injured individuals are taken in, and the remaining (uninjured) members then reach for a shelter (and the group speed is updated accordingly). If the hospital has no vacancy, the group tries to reach another hospital as an individual agent would do.

Examples of groups within the ABM are shown in Figure 1. Group A is a single heavily injured agent waiting to be rescued by an ambulance; group B consists of two un-injured agents that move together to the nearest shelter. Group C is composed by three agents, one of which is lightly injured. Hence, the group heads toward the nearest hospital. Finally, group D represents a group of pedestrians who have succumbed to panic and are moving randomly together across the map until the group's panic time has expired.

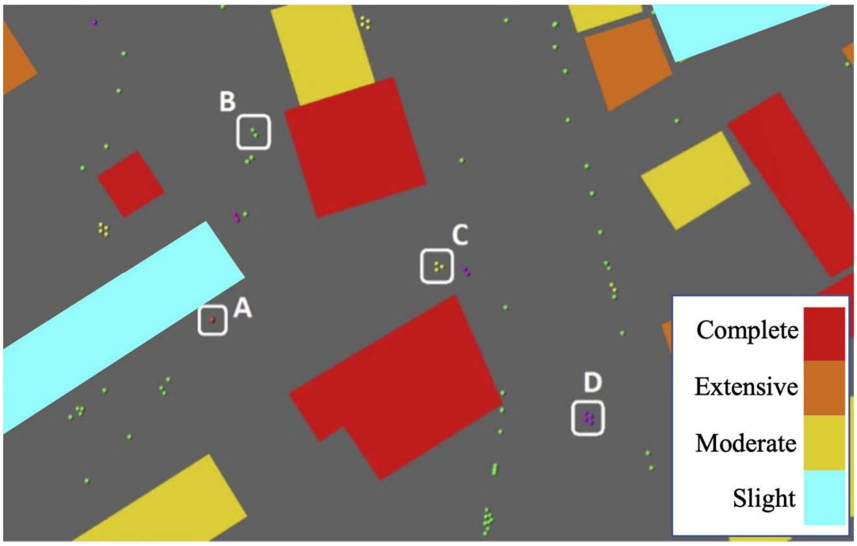

Figure 1. Different groups of agents within the ABM and building damage level.

4 Methodology

This section summarizes the implementation of the IdealCity hybrid model along with the seismic scenarios that have been adopted for the simulations. Details about the implementation of human behavior in the ABM of the virtual city are given in (Battegazzorre et al. 2021).

4.1 Seismic scenarios

Four different seismic scenarios are adopted in this study with the characteristics summarized in Table 2. The Attenuation Ground Motion Prediction Equation (Ambraseys et al. 1996) is used to assess the geometrical attenuation effects related to epicenter-to-building distance (earthquake spatial variability). The seismic scenarios can be classified into two groups by considering the distance from the fault, which are *near-field* and *far-field* earthquakes. In detail, the Northridge and Kobe events (near-field earthquakes) occurred at a distance in the range 10-60 kilometers and show higher acceleration contents and a more limited frequency band with respect to far-field ground motions. The last ones include El Centro and Hachinohe events. The map of the damage experienced by the buildings is depicted in Figure 2. The damage distribution map shows that downtown (the colored part in the figure), mainly composed of old masonry buildings, is the most vulnerable zone. Most of the buildings have experienced slight damage (about 38%), while 30% and 22% of the buildings show moderate and extensive damage, respectively. 3% of the buildings are collapsed and the remaining part is undamaged (about 9%). Further information can be found in (Marasco et al. 2021).

Table 2. Adopted seismic records

Record	Occurrence	Mw	Hypocentral depth [km]	Peak Ground Acceleration [g]
Northridge	1994-01-17	6.7	11.3	0.84
Kobe	1994-01-17	6.8	17.6	0.82
EL Centro	1940-05-18	6.9	16.0	0.35
Hachinohe	1968-05-16	8.2	26.0	0.23

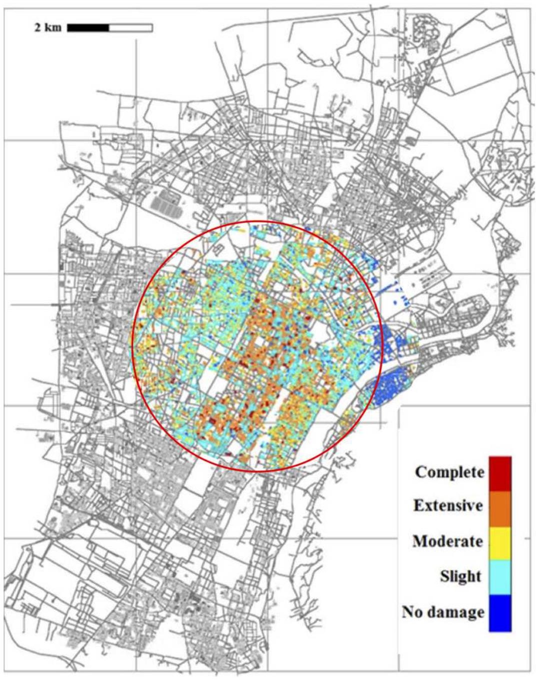

Figure 2. Distribution of buildings within “Ideal City” based on level of damage (adapted from (Marasco et al. 2020)).

4.2 Simulations

The input parameters needed to run the emergency evacuation simulation (i.e., structural damage to buildings and generated debris, as well as blocked roads and their impact on evacuees) have been computed through the approaches presented in previous studies (Domaneschi et al. 2018; Marasco et al. 2021). Each numerical simulation reproduces a seismic scenario occurring at different day times, involving different distribution (indoor and outdoor) of pedestrians in *IdealCity*. As a result, different proportions of the dead, seriously/lightly injured, and trapped agents are computed based on their position within the *IdealCity*. For quantitative evaluation, fine-grained logs are kept for each session (one record per minute of simulation time). The average execution time, the current number of active agents (those ones that are moving in the city toward a shelter or waiting an ambulance to be rescue), the secured agents who reached a safe place or chose to remain near their homes, and the shelters-hospitals occupancy are examples of such collected data. The emergency simulation generates two types of outputs: detailed logs collected during the simulation and near real-time graphics supplied by Unity, a multi-purpose game engine that uses C# as a programming language (Unity Technologies 2017). Specifically, the set of detailed logs is then analyzed to collect the interesting outcomes and the near-real-time visualization enables for interactive city map navigation and zooming tools for deep simulation examination.

5 Simulations results

5.1 Panic and group behavior on the evacuation process

To analyze the effects of agents' group behavior and panic on the evacuation process, several simulations were performed for each possible scenario, combining different group affinity levels and different panic thresholds. Two panic thresholds were defined: a low threshold (0.25, with a higher number of panicked pedestrians) referenced in the following as HiPB (high panic behavior) and a high threshold LoPB (0.5, with a lower number of panicked pedestrians). As for group affinity, two different levels have been defined: a high group affinity HiGA (characterized by a 25% probability that agents are not in a group, a 25% that they are in a group of two, 25% for a group of three, and a 25% for a group of four) and a low group affinity level LoGA (where agents are not in a group with

50% of probability, while groups with two, three or four agents have equal probability of 16.6% each to be generated).

Therefore, for each scenario, four simulations have been run combining the panic thresholds and the group affinities defined before, plus a fifth simulation that does not consider panic and group behaviors that was used as a baseline. All simulations, including the baseline, were run at 2am for each of the four different earthquakes. To sum up, the five simulations for each scenario cover the following combinations:

- Simulation 1 (Baseline): no panic (NoPB) and no group behaviors (NoGB)
- Simulation 2: HiGA - LoPB (groups with more individuals, less panicked agents).
- Simulation 3: HiGA - HiPB (groups with more individuals, more panicked agents).
- Simulation 4: LoGA - LoPB (groups with less individuals, less panicked agents).
- Simulation 5: LoGA - HiPB (groups with less individuals, more panicked agents).

The population response in the emergency evacuation in the five panic state combinations is an important element to investigate by focusing on the time evolution of some of the simulation variables. The number of secured individuals, i.e., those who arrived at their destination, is a key outcome to examine (shelters, hospitals, city exits, etc.).

Figure 3 depicts the data acquired for the secured agents in the five combinations from various seismic occurrences. From the Northridge scenario in particular (the worst damage scenario among the selected ones (Marasco et al. 2020; Battegazzorre et al. 2021)), it can be observed that agents in a panic state and moving in groups take longer to reach their destination. This is a reasonable result as agents affected by panic tend to act less logically and make random decisions before arriving at their destination increasing their total evacuation time. Such behavior is evident in the Northridge scenario where around 800,000 agents with no panic reach a safe place in more than one hour and a half. On the contrary, in the case of HiGA and HiPB, more than 700,000 agents reach a safe place in almost two hours and a half. A similar case can be found in the combination of LoGA and HiPB, where 700,000 agents need the same time (two hours and a half) to be in a safe place. This result can be justified by considering that a low panic state threshold has a higher impact on the evacuation process than group behavior.

Deepening the analysis and focusing on hospitals, Figure 4 depicts their occupation by agents in the five combinations of behaviors. The panic state and the group behavior increase the time of reaching the nearest hospitals. As an example, in the Northridge scenario in case of no panic situations, hospitals are filled in less than one hour; while if agents are affected by panic and show a group behavior, that fill limit becomes one hour and a half. Furthermore, in all scenarios without panic behavior, in less than an hour, the hospital's nominal capacity is reached (except in the case of Hachinohe, where the number of slight injured is smaller than the number of places available). Thus, wounded people that cannot find medical assistance in other facilities, move towards the field hospital. In case of panic behavior and group behavior, instead, in all the scenarios (exception made for Hachinohe) hospital nominal capacity leads to saturation in more than one hour, as agents affected by panic tend to move around the city developing blind and irrational actions before reaching their destination.

The occupation of shelters is reported in Figure 5. In all the simulations, without considering the panic behavior and the group behavior, in less than an hour, all shelters are full. On the contrary, considering the panic behavior and the group behavior of the individuals, the time necessary to fill the emergency shelters increases in all the considered scenarios. As an example, in the Northridge scenario, it is evident that in case of noGB and noPB, HiGA and LoPB, and LoGA and LoPB, 100,000 agents can reach the shelters in 30 minutes. In the case of HiGA and HiPB, the same number of agents require 50 minutes to reach the shelters. Finally, the same number of agents need more than one hour to reach the shelters in the scenario LoGA and HiPB (the worst-case scenario). All the remaining individuals who did not suffer injuries, or otherwise did not have their health compromised, have as their only choice to leave the city. By looking at the results carried out from the simulations, it is possible to state that the panic condition of the individuals mainly influences the evacuation process, while the group behavior has a less contribution. This can be justified by looking at the number of secured agents (both in hospitals and in shelters) in relation to simulation time (see Figure 4 and Figure 5). This is more evident in seismic events with severe damage to buildings (i.e., ElCentro, Northridge) and, in turn, more agents around the city. Cases with HiPB are those with the longer evacuation times and, in turn, the case with HiGA but LoPB is much closer to the control case (NoPB, NoGA), meaning that PB influences evacuation times to a greater extent when compared to GA. The same can be observed in all scenarios, but to a lesser extent.

It can be observed from Figure 4 for the Northridge or the El Centro scenarios with more emphasis, where the cases with HiPB are those ones with the longest evacuation time, regardless of the type of group behavior. This outcome highlights the danger of falling into a state of panic, since the average time to reach a safe location is noticeably longer, even when paired with group movement, which should *reduce* the time to reach a shelter or hospital.

Figure 3. Secured agents for the five combinations and different seismic scenarios

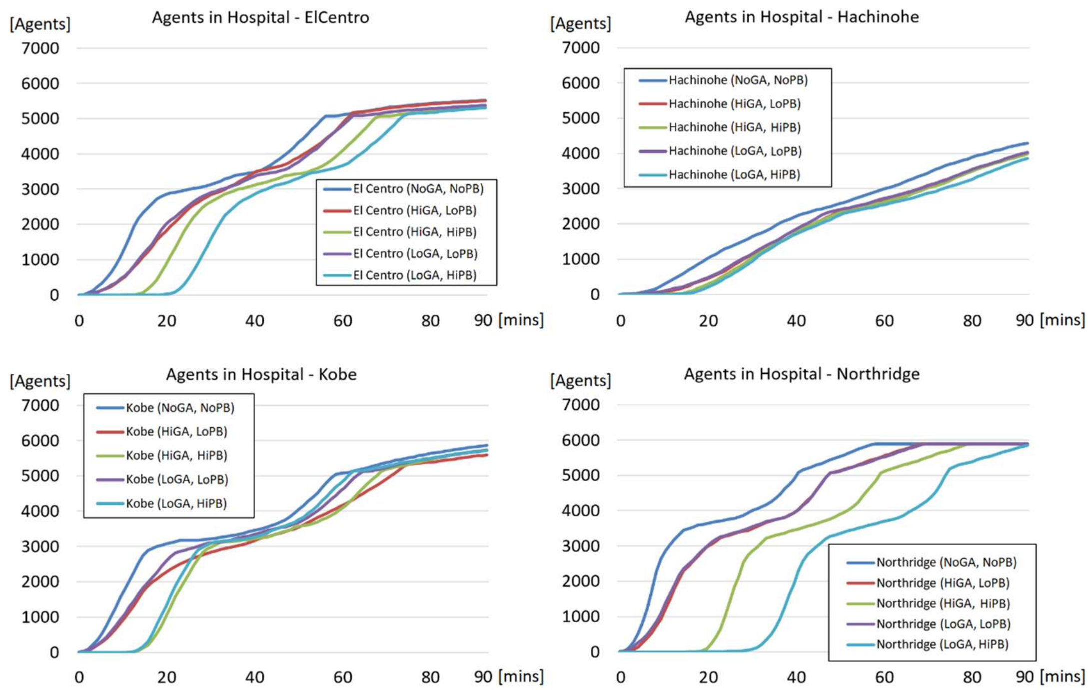

Figure 4. Occupation of Hospitals based on the five combinations for different seismic scenarios

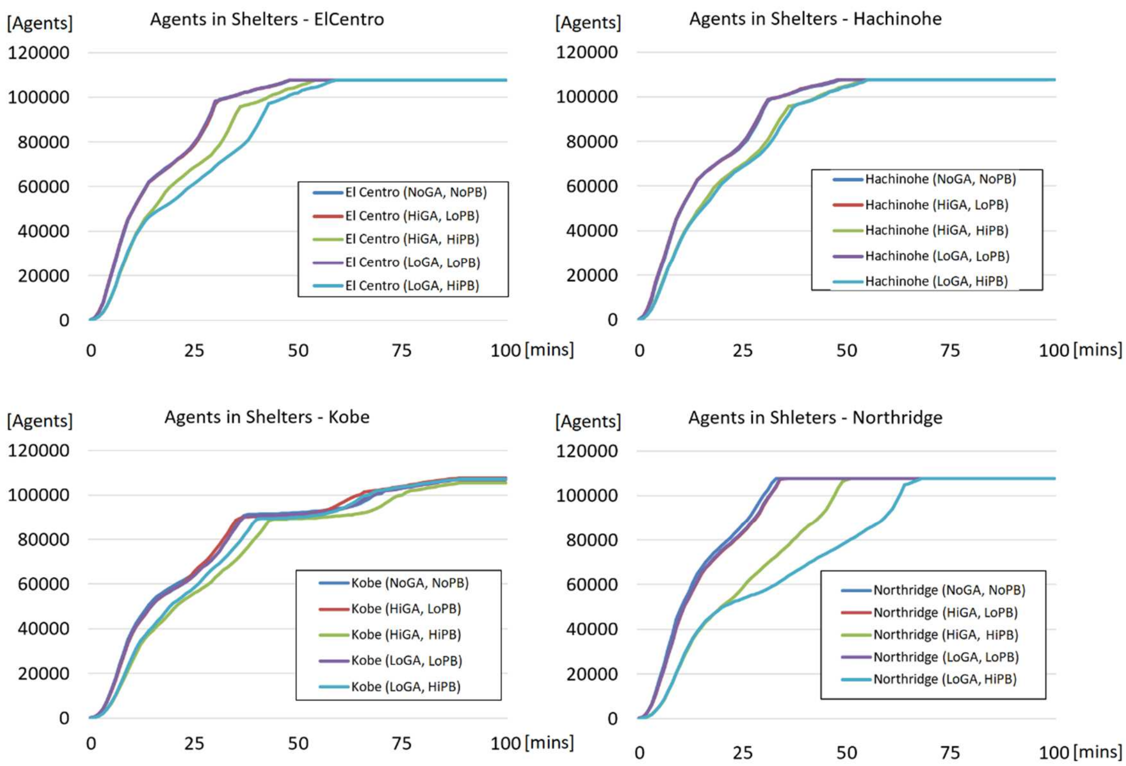

Figure 5. Occupation of Shelters based on the five combinations for different seismic scenarios

5.2 Emergency response analysis of critical facilities

The proposed model enables analyzing the most critical facilities (i.e., shelters and hospitals) in terms of emergency response at the local scale where they are placed. This is done by evaluating the saturation index of each emergency facility for the evaluated simulation conditions (agents with no panic and agents under panic conditions coupled with group behavior). The saturation index of a facility is expressed in terms of *unsecured agents*, as Equation 7:

$$Unsecured\ agents = Influenced\ agents - occupants - stay\ home\ agents \qquad (7)$$

where:

- *influenced agents:* it is assumed that for each building in the city, the agents are trying to reach the nearest hospital and emergency shelter and this information is known to each agent. From another perspective, each building is added to the area of influence of the nearest hospital/shelter. The number of *influenced agents* depends on the type of critical buildings. For shelters, it is the sum of uninjured agents residing in buildings at least slightly damaged residing in the shelter's area of influence. For hospital, it is the total sum of lightly and heavily injured agents living in the hospital's area of influence.

- *occupants:* the maximum number of occupants for a critical building (i.e., hospital and emergency shelter).

- *stay home agents:* the number of agents in the shelter's area of influence that live in an undamaged building and are uninjured, so they stay home rather than evacuating (for shelters only, since all injured agents try to reach a hospital).

Note that the number of unsecured agents can be either positive or negative, as explained below:

- *Unsecured agents* > 0: the critical building is unable to accommodate all agents in its area of influence.

- *Unsecured agents* = 0: the critical building accommodates all agents in its area of influence.

- *Unsecured agents* < 0: the critical building accommodates all agents in its area of influence and agents from other areas.

After calculating the number of *unsecured agents*, it is possible to compute the number of secured agents normalized between 0 and 1 as Equation 8.

$$normalized\ secured\ agents = 1 - (\frac{unsecured\ agents}{influenced\ agents}) \quad (8)$$

Table 3 and Table 4 list the normalized number of secured agents for shelters and hospitals placed in IdealCity. The results shown in this table can be used to assess if shelters and hospitals are appropriately sized and/or sensibly placed in the city. If the city was perfectly organized in terms of emergency facilities, all the results should be very close to one. A facility with a normalized value less than one means that the people that end up in that facility are less than the people that need to be recovered and are under that facility's area of influence, implying that either the shelter is too small, or there are too few shelters in that area. Conversely, a value greater than one (possible if the number obtained with Equation (7) for unsecured agents is negative) means that the capacity of the shelter, and the number of those who can stay at home, is greater than the *influenced agents*. This implies that the shelter is too large for the specific area, or even that there may be too many shelters in the affected area.

The indication "NA" in Table 3 for hospitals I and M means "Not Applicable". This is caused by the fact that there is a very high density of hospitals in those areas and, as a result, the normalized values of secured agents would be disproportionate. Moreover, the presence of a field hospital with almost unlimited capacity at facility M makes the calculation of the coefficient further unjustified.

Table 3. Normalized values of secured agents in shelters in different scenarios

Shelter ID	El Centro	Hachinohe	Kobe	Northridge
01	0.42	0.41	0.58	0.05
02	1.54	1.47	1.61	1.23
03	0.58	0.79	0.96	0.32
04	0.33	0.49	0.72	0.09
05	0.84	0.66	0.84	0.47
06	0.42	0.63	0.88	0.15
07	0.47	0.41	0.79	0.07

08	0.28	0.37	0.52	0.10
09	3.97	3.94	4.18	4.10
10	0.63	0.56	0.84	0.10
11	0.41	0.56	0.73	0.09
12	0.42	0.39	0.74	0.11
13	0.27	0.31	0.75	0.06
14	0.26	0.32	0.73	0.09
15	0.19	0.48	0.64	0.04
16	0.37	0.32	0.78	0.06
17	0.44	0.44	0.79	0.16
18	0.35	0.35	0.75	0.06
19	0.73	0.79	0.93	0.15
20	0.37	0.28	0.59	0.17
21	0.43	0.50	0.77	0.05
22	0.26	0.39	0.74	0.07
23	0.33	0.39	0.59	0.09
24	0.54	0.53	0.86	0.13
25	0.67	0.64	1.02	0.33
26	0.70	0.64	0.92	0.23
27	0.68	0.61	0.80	0.35
28	0.68	0.56	0.88	0.24
29	1.06	1.12	1.31	0.59
30	1.63	1.09	1.82	1.24
31	1.13	1.09	1.33	0.74

Table 4. Normalized values of secured agents in hospitals in different scenarios

Hospital	El Centro	Hachinohe	Kobe	Northridge
A	0.01	0.03	0.01	0.00
B	0.84	8.45	0.59	0.17
C	1.71	1.25	1.25	0.51
D	0.24	20.33	0.20	0.09
E	0.28	0.44	0.11	0.04
F	0.41	3.36	0.26	0.06
G	2.46	64.00	2.21	0.57
H	0.47	1.02	0.31	0.18
I	NA	NA	NA	NA
J	0.09	0.23	0.06	0.02
K	0.08	0.56	0.06	0.03
L	0.09	4.18	0.06	0.02
M	NA	NA	NA	NA
N	0.24	3.13	0.25	0.05
O	0.37	1.16	0.32	0.11
P	0.09	0.61	0.06	0.02

Results of the simulations for Northridge and El Centro seismic scenarios are depicted in Figure 6. Shelters and hospitals are marked through a color-graded scale as function of the number of secured agents. This type of visualization allows planners to quickly identify the metropolitan district that requires more resources in the event of a crisis. It can be noticed that hospitals and shelters located in densely populated urban areas, such as Hospital A and Shelter number 26, have a low saturation index due to their reduced capacity. It means that its capacity does not satisfy the number of influenced agents and it needs to be improved. On the other hand, hospitals like G with a very high saturation index (especially in a less severe scenario like Hachinohe, with relatively few injured agents) can be interpreted as redundant, since they are placed in an area which is either less vulnerable or scarcely populated (both are true for hospital G).

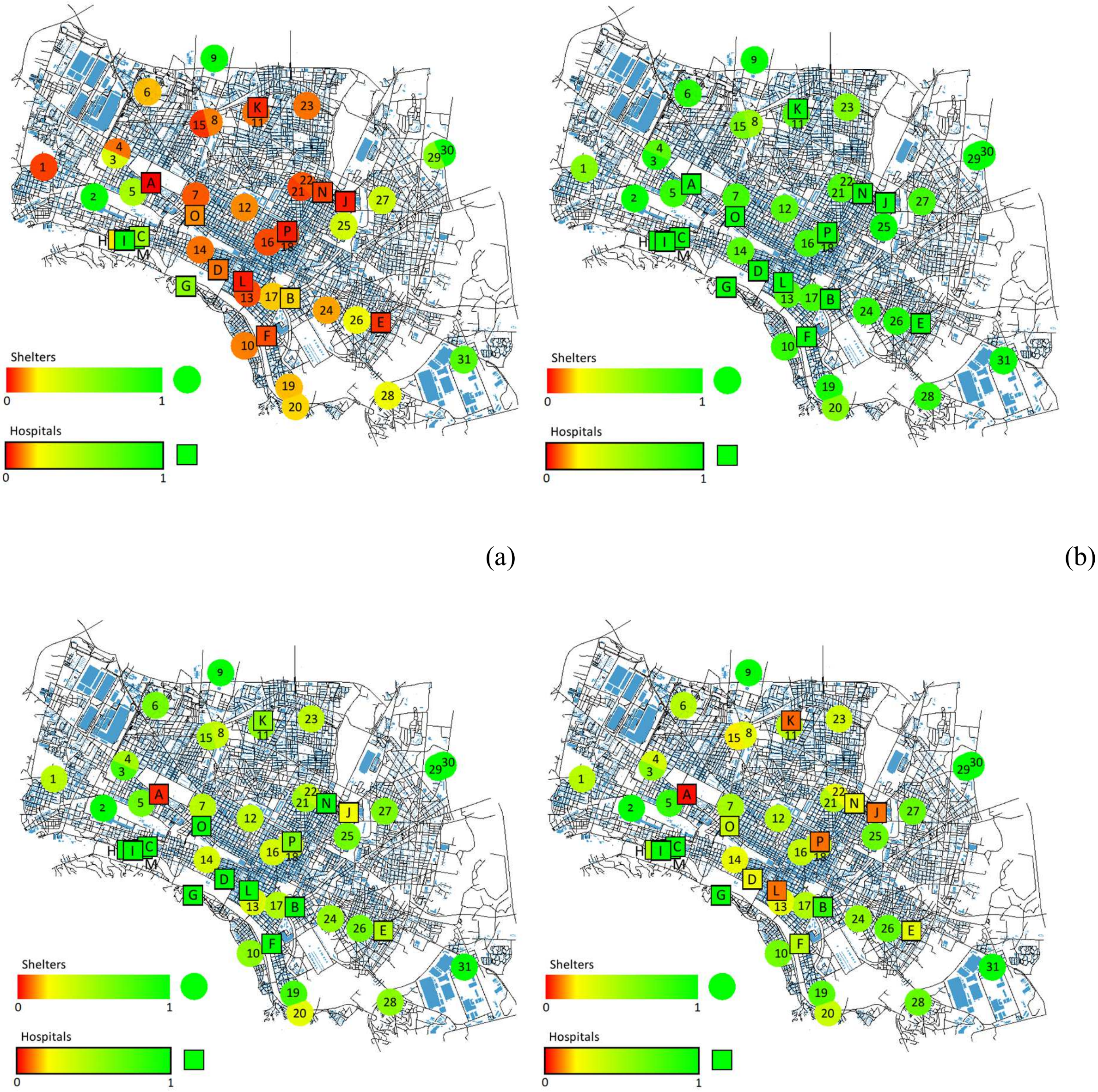

Figure 6. Saturation index of the emergency facilities in: (a) Northridge scenario, (b) Kobe scenario, (c) Hachinohe scenario, and (d) El Centro scenario (circles: shelters; squares: hospitals).

6 Concluding remarks

A human behavior model is proposed in this paper that has been integrated into an agent-based model to simulate and study the evacuation process at the city scale. The panic behavior model considers the building damage level, the generated debris with the resulting interrupted roads, and the injured individuals. Furthermore, the human group behavior is implemented within the evacuation model to consider its effect on the evacuation time together with the saturation of emergency facilities (i.e., shelters and hospitals). The model has been tested in a realistic urban environment, considering several seismic scenarios and different combinations of panic conditions and group behaviors.

The negative impact of the panic condition on the evacuation process has been clearly observed, while collective behavior, although not facilitating the evacuation process, does have a lower influence. However, our model only considers static groups formed when agents leave a building. To further study the phenomenon, future works could consider larger (>4) and dynamic groups merging and/or disbanding during the evacuation process. Also, all the agents move on foot in our study, so movement with vehicles could be a worthy inclusion in future studies. Indeed, during the evacuation process, the panic level speeds up the actual velocity of pedestrians. However, the agents make blind and irrational actions before reaching their destination increasing the evacuation process (*faster-is-slower* phenomena). In all scenarios, the occupation of hospitals and emergency shelters is slow for panic-cases compared to the non-panic case.

The saturation index of the emergency facilities has been estimated by considering their capacity, vulnerability, and density. It can support decision-makers in the implementation and prioritization of specific interventions to improve community resilience. Future works will be oriented to validate the model through different real environments beyond the adopted virtual city and seismic scenarios.

7 Acknowledgments

This work was supported by the European Research Council under the Grant Agreement nr. ERC IDEAL RESCUE 637842 of the project IDEAL RESCUE – Integrated Design and Control of Sustainable Communities during Emergencies.

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