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Large scale simulation of pedestrian seismic evacuation including panic behavior

Melissa De Iuliis^a, Edoardo Battezzorre^b, Marco Domaneschi^c, Gian Paolo Cimellaro^{c*}, Andrea Giuseppe Bottino^b

^aDept. of Structural and Geotechnical Engineering, Sapienza University of Rome, Via Eudossiana, 18, Rome, Italy

^b Dept. of Control and Computer Engineering, Politecnico di Torino, Corso Duca degli Abruzzi, 24, Torino, Italy

^cDept. of Structural, Geotechnical and Building Engineering, Politecnico di Torino, Corso Duca degli Abruzzi, 24, Torino, Italy, *Corresponding author: gianpaolo.cimellaro@polito.it

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.

31 1 Introduction

32 Many unexpected disasters, such as hurricanes, earthquakes, floods, and landslides, have impacted
33 on communities in recent years. As urbanization increases, the complexity of infrastructures (e.g.,
34 buildings, transportation, and distribution networks) and their interconnections also continues to
35 grow. Researchers are primarily interested in simulating and evaluating the population's response in
36 emergency evacuation situations to improve evacuation strategies, minimize evacuation time, and
37 decrease the number of casualties and injuries (Mikulik et al. 2014; Meng & Jia 2017; Wang et al.
38 2020). Current crowd simulation approaches can be divided into three categories: *flow-based*, *entity-*
39 *based*, and *agent-based* (Qiu & Hu 2010; Zhou et al. 2010). The first one neglects individual
40 characteristics in large-size crowds as it treats the crowd. The second method builds crowd
41 simulations without taking individual behavior into account. Finally, *agent-based models* (ABMs)
42 represent the individuals as agents and define their behaviors and characteristics through a set of rules
43 associated with each agent type (Bonabeau 2002). Recently, ABMs have been frequently applied to
44 quantify community resilience to natural and human-caused disasters (Solís & Gazmuri 2017). ABMs
45 allow a computational description at the level of analysis of agents, interactions of the agents, and
46 they can help to verify the agents' behaviors (Squazzoni 2014). For instance, Kang et al. (2022)
47 proposed an ABM to simulate stochastic occupant movement in buildings by using Immersive Virtual
48 Environments (IVEs). Bina & Moghadas (2021) applied a BIM software with the human behavior
49 simulation engine (AnyLogic code) upon the ABM to simulate emergency evacuation from a
50 conference hall. A novel ABM that incorporates the social dimension of group loyalty into fire
51 evacuation was proposed by Young & Aguirre (2021). Bernardini et al. (2021) tried to analyzed how
52 the pedestrian evacuation behaviors can affect the emergency strategies. Lumbroso & Davison (2018)
53 described the use of an ABM to evaluate the effectiveness of emergency management interventions
54 accounting for the physical parameters of the agents. Sreejith & Sinimole (2022) studied the
55 pedestrian evacuation process by considering the demographic, geographical, and behavioral aspects.

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

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

62 Recently, a limited number of studies available in the literature include panic behavior in ABMs.
63 Hassanpour & Rassafi (2021) introduced a prototype of ABM using the affordance concept to
64 simulate the decision-making process during an emergency evacuation. The approach was tested to
65 model the behavior of agents in a subway through normal and emergency condition. Abu Bakar et al.
66 (2016) designed a dynamic ABM to simulate the panic behavior models during stressful events.

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

82 human behavior model adopted in this work. Section 4 describes the implementation of the IdealCity
83 hybrid model along with the seismic scenarios adopted for the emergency evacuation simulations.
84 Section 5 presents and discuss the results of the simulations. Finally, conclusions are drawn in Section
85 6 together with the proposed future work.

86 **2 Emergency evacuation modeling**

87 **2.1 Ideal City**

88 IdealCity is a hybrid model that can be adopted as a general framework to simulate cities with
89 different features such as building categories, infrastructure systems, and their interdependencies. The
90 virtual city includes the Socio-Technical Network (STN) response (e.g., emergency rescue and
91 evacuation), which is composed of an ABM capable of managing the entire city population. The city
92 model used in this work reflects the characteristics, such as road transportation network, building
93 type, year of construction, height classifications, and occupation of the town of Turin in Italy. The
94 urban area of Turin is about 130 km² and the city has more than 900,000 inhabitants. Further
95 information can be found in Marasco et al. (2020); Battezzorri et al. (2021). The ABM has two
96 types of agents: *individuals* living in IdealCity and *ambulances* that are supposed to rescue severely
97 injured people and transport them to hospitals (Battezzorri et al. 2021). Other included systems are
98 the *city buildings*, *shelters*, and *hospitals*. Shelters and hospitals have a certain and well-defined
99 capacity; beyond which they cannot accept new agents. Each person in indoor environments has a
100 health condition: *healthy*, *lightly injured* (the ability to walk is maintained), *severely injured* (the
101 agent can't move autonomously and requires the assistance of an ambulance), or *dead*. The outdoor
102 agents, on the other hand, are randomly positioned along IdealCity, and their health condition is
103 determined by their proximity to the rubble of the damaged buildings.

104 **2.2 Damage of buildings**

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

109 An innovative surrogate model capable of representing the response of thousands of multi-story
110 buildings in the virtual city named as IdealCity is employed to reduce the computational efforts.
111 Indeed, the surrogate model allows the number of degrees of freedom of seismic analysis to be
112 drastically limited, without decreasing the degree of seismic response prediction (Domaneschi et al.
113 2018; Marasco et al. 2021). The surrogate model predicts the expected per-building damage level
114 (from none to complete (HAZUS 2015)), the amount of debris produced and to what extent this may
115 affect the availability and efficiency of the urban transportation network.

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

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

129 regression line computed by the ML algorithm. As a result, the lower the MARD, the more precise
130 the prediction.

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

137 **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

138

139 **3 Human behavior modeling**

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

147 In general, panic behavior can be analyzed at different levels (Pan et al. 2007). At the micro-level,
148 individual behavior is influenced by physical and mental factors. Physical parameters include age,
149 gender, current location and speed, and health status. Mental factors include knowledge about the

150 environment, agent's emotions (e.g., sadness, fear, anger), agent's experience, and so on. At the
151 macro-level, an agent's decision-making process is influenced by three main factors: instinct,
152 experience, and bounded rationality (Pan et al. 2007; Şahin et al. 2019). The simplest way to respond
153 to an event in an emergency is instinct because it does not require the involvement of the conscious
154 component of intellect. Moreover, two factors can increase individuals' panic and stress levels, and
155 reduce their ability to make rational decisions: namely crowd density and environmental constraints,
156 e.g. the presence of stairs or doorways in indoor environments (Pan et al. 2007).

157 Focusing on the group behavior modeling, the interactions between individuals in the group can be
158 either cooperative or competitive. For example, an individual may decide to follow a leader who
159 shows greater leadership qualities or to isolate herself to avoid collisions with others (Sharma et al.
160 2016). Under these conditions, it is also necessary to consider the cohesion between group members,
161 which is certainly stronger in the case of friendship or family relationships that lead to the creation
162 of micro-groups, often with two to four members. This cohesion persists even in emergencies and
163 group members tend to stay together rather than flee alone (Drury et al. 2009). Furthermore, it has
164 been found that individuals within a cohesive group are more likely to make evacuation choices that
165 are better for the group as a whole (Sime 1983).

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

175 tend to move in the direction where they expect to find safety. However, their movement is irrational
176 as long as they are panicked (Helbing & Johansson 2013).

177 **3.1 Agent behavior**

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

186 **3.1.1 Panic behavior**

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

$$189 \quad pl = (a \cdot k_a + b \cdot k_b + c \cdot k_c + d \cdot k_d) \quad (1)$$

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

193 In detail, a is a randomized number that accounts for the agent's *predisposition to panic* (Lu et al.
194 2019), while b is obtained from the mean injury level (il) of other individuals in the immediate vicinity
195 of the agent (i.e. in the same building for indoor agents, or within a small radius, defined as a
196 simulation parameter for outdoor agents). Parameter b is computed as Equation 2.

197

$$198 \quad b = \frac{\sum_{i=1}^N il_i}{N} \quad (2)$$

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

202 The c parameter reflects the amount of debris that covers and blocks the evacuation path; it depends
203 directly on the average damage level dl of the buildings in which indoor agents are located and in the
204 immediate vicinity of the outdoor agent (according to suitable threshold, e.g., a circular area of radius
205 25m around the outdoor agent). The formula for c consists in Equation 3.

$$206 \quad c = \frac{\sum_{i=1}^M dl_i}{M} \quad (3)$$

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

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

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

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

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

233 As for the duration of a panic attack, this lasts between 5 and 20 minutes according to (Barlow et al.
234 1994; Healthwise Staff 2020). Therefore, in the simulations, if a panic attack is triggered, its duration
235 is computed as a function of the panic level pl (Equation 4).

$$236 \quad \text{panic time} = 5mins + (pl * 15 mins) \quad (4)$$

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

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

$$243 \quad v_a(t) = v_{a0}(1 + pe(t)) \quad (5)$$

244 where v_{a0} is the agent's walking speed, without considering panic and $pe(t)$ is the panic effect on (i.e.,
245 increase in) walking speed at time t due to panic. The walking speed v_{a0} is a function of the amount
246 of debris on the streets (Lu et al. 2019) and the agent's age and degree of injury computed as follows.
247 The initial pedestrian "normal" speed v_{a0} is randomly chosen from a range between a normal
248 (comfort) and a peak (maximum) walking speed depending on age and gender (Bohannon 1997).
249 Then, light injuries affect the agent's walking abilities, reducing v_{a0} by a varying arbitrary percentage

250 between [40% and 80%] (see (Battezzorre et al. 2021) for details). As for $pe(t)$, its value decreases
251 exponentially over time according to the following Equation 6.

$$252 \quad pe(t) = \begin{cases} pl * (1 - e^{(-ln2/t)}), & t < \textit{panic time} \\ 0, & t \geq \textit{panic time} \end{cases} \quad (6)$$

253

254 **3.1.2 Group Behavior**

255 Group behaviors (GBs) are examples of social collective behaviors because they often have social
256 and cultural manifestations. This behavior occurs when some evacuees are faced with uncertainty
257 about what is going on and what they can do to protect themselves and others they care about (Cialdini
258 1993; Pan 2006). In such a situation, evacuees who are uncertain about which path to take may choose
259 to follow others who appear to be acting more deliberately. Self-organized social systems develop
260 stable patterns of interaction among participants (Parsons & Shils 2017). Mann (1969) pointed out
261 that group cohesion is achieved when informal rules are established that allow individual members
262 to conform to the behavioral pattern of the collective.

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

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

275 - the role of “group leader” is assigned to the member with the lowest *panic level*. The *panic level*
276 of the leader determines the panic level of the group and thus, according to the rules described
277 above, whether the group is affected by a panic attack.

278 - The overall speed of the group is set to that of its slowest member. For example, an elderly or
279 injured person affects the evacuation speed of everyone in the group.

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

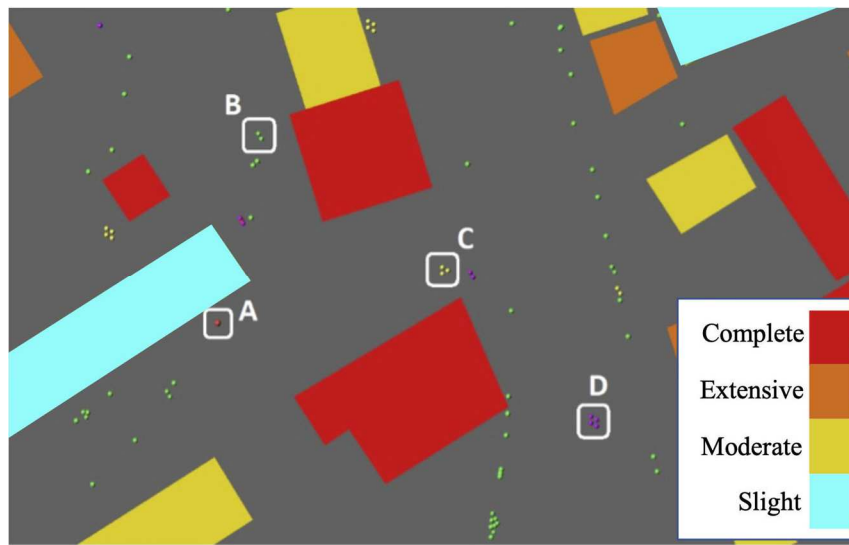
281 1. *Random destination*: if the group leader has succumbed to panic, the group moves erratically as
282 described in the previous section for individual agents.

283 2. *Shelter*: if not in panic and everyone in the group is uninjured, the group tries to reach the nearest
284 safe shelter. If the shelter is full, members search for another shelter with vacancies or leave the
285 city as individual agents would. (Note: in the borderline case where, for example, a group of four
286 reaches a shelter with only three vacant spots, it has been assumed that shelter operators would
287 be unwilling to divide a family and they are taken in regardless of the currently available places.
288 Technically the maximum capacity of a shelter could be exceeded by a maximum of three
289 individuals, however, this is not a problem since such occurrences can be expected in the chaos
290 of an emergency)

291 3. *Hospital*: if at least one of the members is lightly injured, the group moves towards the closest
292 hospital. Once a hospital with a vacancy is reached, the injured individuals are taken in, and the
293 remaining (uninjured) members then reach for a shelter (and the group speed is updated
294 accordingly). If the hospital has no vacancy, the group tries to reach another hospital as an
295 individual agent would do.

296 Examples of groups within the ABM are shown in Figure 1. Group A is a single heavily injured agent
297 waiting to be rescued by an ambulance; group B consists of two un-injured agents that move together
298 to the nearest shelter. Group C is composed by three agents, one of which is lightly injured. Hence,
299 the group heads toward the nearest hospital. Finally, group D represents a group of pedestrians who

300 have succumbed to panic and are moving randomly together across the map until the group's panic
301 time has expired.



302
303 **Figure 1.** Different groups of agents within the ABM and building damage level.

304 **4 Methodology**

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

308 **4.1 Seismic scenarios**

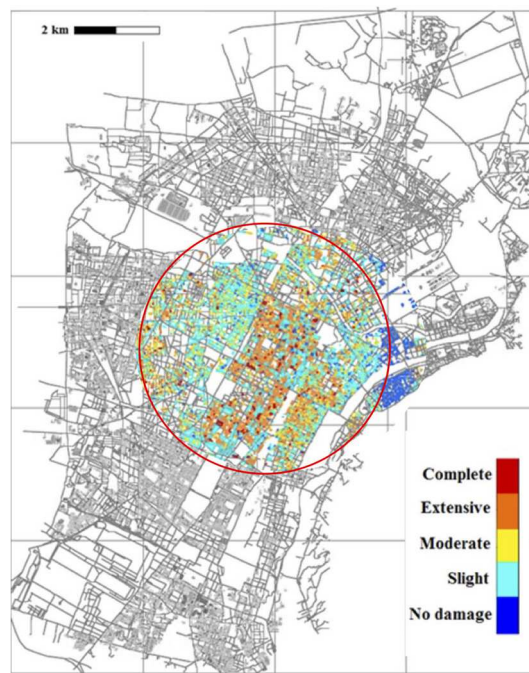
309 Four different seismic scenarios are adopted in this study with the characteristics summarized in Table
310 2. The Attenuation Ground Motion Prediction Equation (Ambraseys et al. 1996) is used to assess the
311 geometrical attenuation effects related to epicenter-to-building distance (earthquake spatial
312 variability). The seismic scenarios can be classified into two groups by considering the distance from
313 the fault, which are *near-field* and *far-field* earthquakes. In detail, the Northridge and Kobe events
314 (near-field earthquakes) occurred at a distance in the range 10-60 kilometers and show higher
315 acceleration contents and a more limited frequency band with respect to far-field ground motions.
316 The last ones include El Centro and Hachinohe events. The map of the damage experienced by the

317 buildings is depicted in Figure 2. The damage distribution map shows that downtown (the colored
 318 part in the figure), mainly composed of old masonry buildings, is the most vulnerable zone. Most of
 319 the buildings have experienced slight damage (about 38%), while 30% and 22% of the buildings show
 320 moderate and extensive damage, respectively. 3% of the buildings are collapsed and the remaining
 321 part is undamaged (about 9%). Further information can be found in (Marasco et al. 2021).

322 **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

323



324

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

327 4.2 Simulations

328 The input parameters needed to run the emergency evacuation simulation (i.e., structural damage to
 329 buildings and generated debris, as well as blocked roads and their impact on evacuees) have been
 330 computed through the approaches presented in previous studies (Domaneschi et al. 2018; Marasco et

331 al. 2021). Each numerical simulation reproduces a seismic scenario occurring at different day times,
332 involving different distribution (indoor and outdoor) of pedestrians in *IdealCity*. As a result, different
333 proportions of the dead, seriously/lightly injured, and trapped agents are computed based on their
334 position within the *IdealCity*. For quantitative evaluation, fine-grained logs are kept for each session
335 (one record per minute of simulation time). The average execution time, the current number of active
336 agents (those ones that are moving in the city toward a shelter or waiting an ambulance to be rescue),
337 the secured agents who reached a safe place or chose to remain near their homes, and the shelters-
338 hospitals occupancy are examples of such collected data. The emergency simulation generates two
339 types of outputs: detailed logs collected during the simulation and near real-time graphics supplied
340 by Unity, a multi-purpose game engine that uses C# as a programming language (Unity Technologies
341 2017). Specifically, the set of detailed logs is then analyzed to collect the interesting outcomes and
342 the near-real-time visualization enables for interactive city map navigation and zooming tools for
343 deep simulation examination.

344 **5 Simulations results**

345 **5.1 Panic and group behavior on the evacuation process**

346 To analyze the effects of agents' group behavior and panic on the evacuation process, several
347 simulations were performed for each possible scenario, combining different group affinity levels and
348 different panic thresholds. Two panic thresholds were defined: a low threshold (0.25, with a higher
349 number of panicked pedestrians) referenced in the following as HiPB (high panic behavior) and a
350 high threshold LoPB (0.5, with a lower number of panicked pedestrians). As for group affinity, two
351 different levels have been defined: a high group affinity HiGA (characterized by a 25% probability
352 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
353 25% for a group of four) and a low group affinity level LoGA (where agents are not in a group with

354 50% of probability, while groups with two, three or four agents have equal probability of 16.6% each
355 to be generated).

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

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

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

370 Figure 3 depicts the data acquired for the secured agents in the five combinations from various seismic
371 occurrences. From the Northridge scenario in particular (the worst damage scenario among the
372 selected ones (Marasco et al. 2020; Battezzozze et al. 2021)), it can be observed that agents in a
373 panic state and moving in groups take longer to reach their destination. This is a reasonable result as
374 agents affected by panic tend to act less logically and make random decisions before arriving at their
375 destination increasing their total evacuation time. Such behavior is evident in the Northridge scenario
376 where around 800,000 agents with no panic reach a safe place in more than one hour and a half. On
377 the contrary, in the case of HiGA and HiPB, more than 700,000 agents reach a safe place in almost
378 two hours and a half. A similar case can be found in the combination of LoGA and HiPB, where
379 700,000 agents need the same time (two hours and a half) to be in a safe place. This result can be

380 justified by considering that a low panic state threshold has a higher impact on the evacuation process
381 than group behavior.

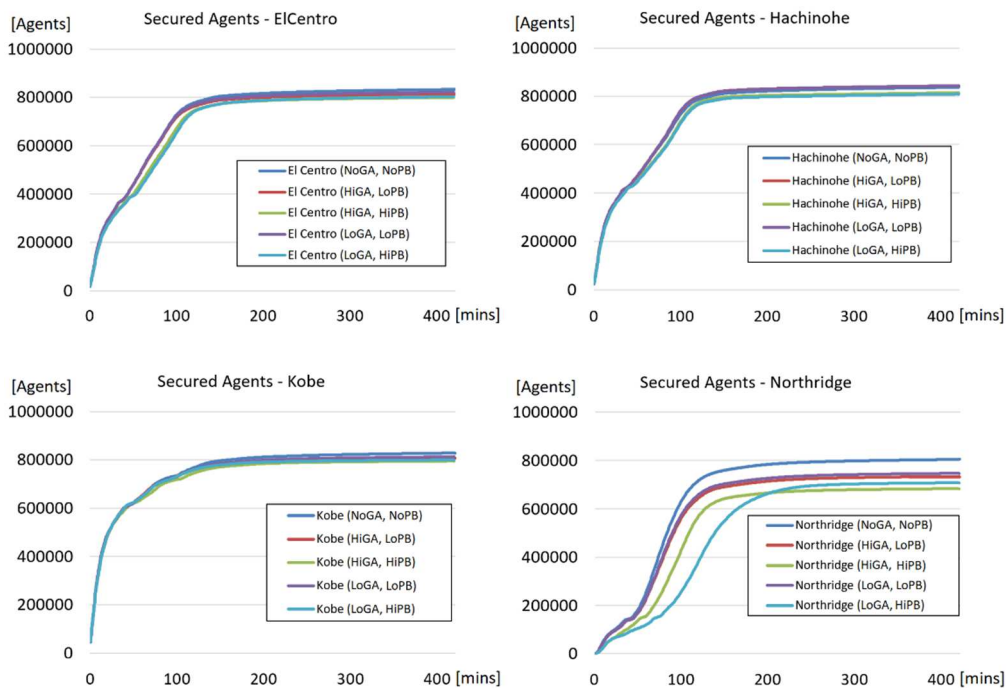
382 Deepening the analysis and focusing on hospitals, Figure 4 depicts their occupation by agents in the
383 five combinations of behaviors. The panic state and the group behavior increase the time of reaching
384 the nearest hospitals. As an example, in the Northridge scenario in case of no panic situations,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

394 The occupation of shelters is reported in Figure 5. In all the simulations, without considering the
395 panic behavior and the group behavior, in less than an hour, all shelters are full. On the contrary,
396 considering the panic behavior and the group behavior of the individuals, the time necessary to fill
397 the emergency shelters increases in all the considered scenarios. As an example, in the Northridge
398 scenario, it is evident that in case of noGB and noPB, HiGA and LoPB, and LoGA and LoPB, 100,000
399 agents can reach the shelters in 30 minutes. In the case of HiGA and HiPB, the same number of agents
400 require 50 minutes to reach the shelters. Finally, the same number of agents need more than one hour
401 to reach the shelters in the scenario LoGA and HiPB (the worst-case scenario). All the remaining
402 individuals who did not suffer injuries, or otherwise did not have their health compromised, have as
403 their only choice to leave the city. By looking at the results carried out from the simulations, it is
404 possible to state that the panic condition of the individuals mainly influences the evacuation process,
405 while the group behavior has a less contribution. This can be justified by looking at the number of

406 secured agents (both in hospitals and in shelters) in relation to simulation time (see Figure 4 and
 407 Figure 5). This is more evident in seismic events with severe damage to buildings (i.e., ElCentro,
 408 Northridge) and, in turn, more agents around the city. Cases with HiPB are those with the longer
 409 evacuation times and, in turn, the case with HiGA but LoPB is much closer to the control case (NoPB,
 410 NoGA), meaning that PB influences evacuation times to a greater extent when compared to GA. The
 411 same can be observed in all scenarios, but to a lesser extent.

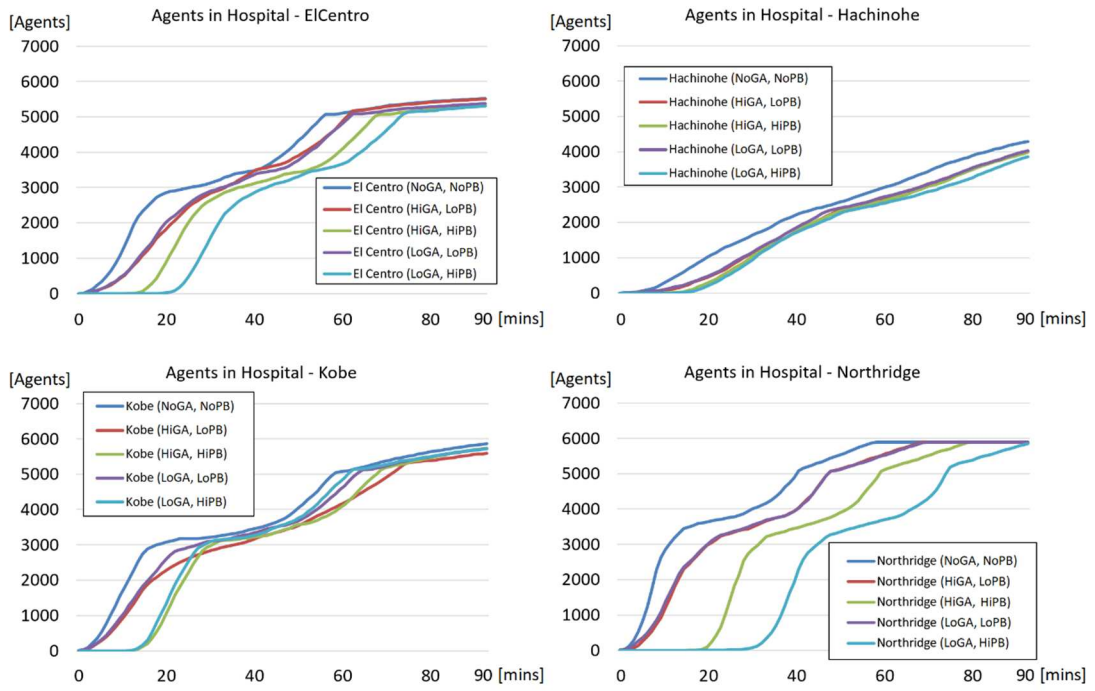
412 It can be observed from Figure 4 for the Northridge or the El Centro scenarios with more emphasis,
 413 where the cases with HiPB are those ones with the longest evacuation time, regardless of the type of
 414 group behavior. This outcome highlights the danger of falling into a state of panic, since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

417



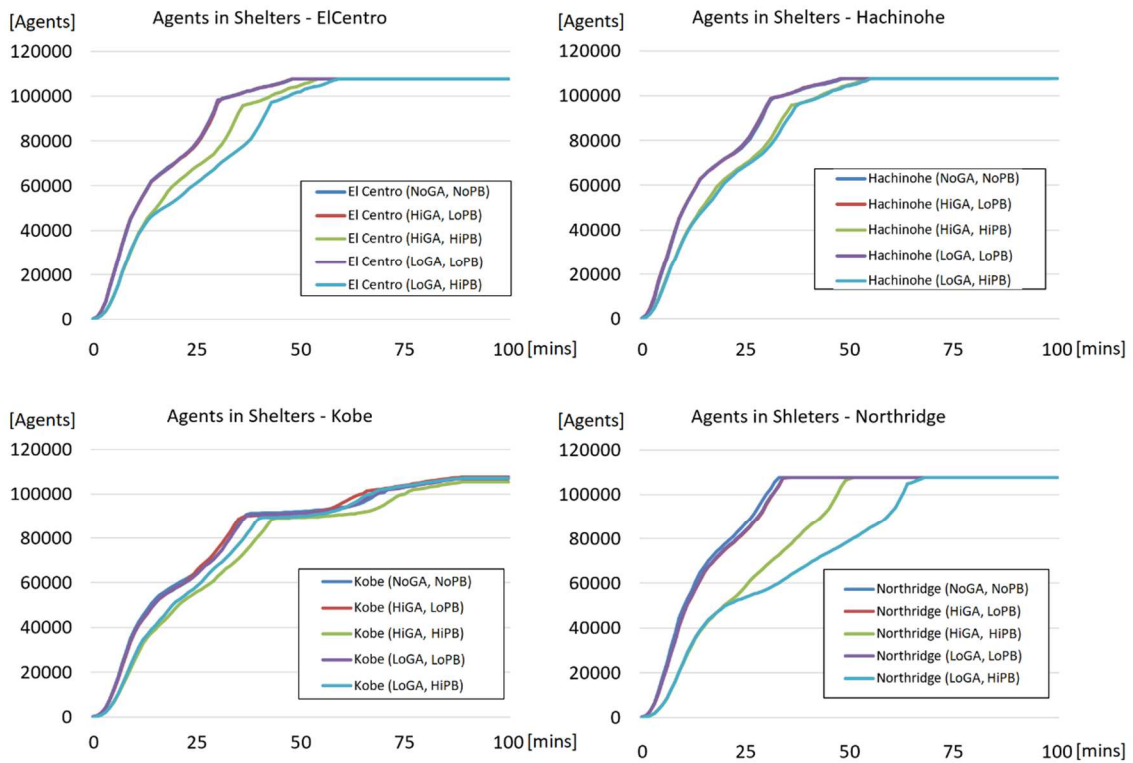
418

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



420

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



422

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

424 **5.2 Emergency response analysis of critical facilities**

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

$$430 \quad \textit{Unsecured agents} = \textit{Influenced agents} - \textit{occupants} - \textit{stay home agents} \quad (7)$$

431 where:

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

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

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

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

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

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

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

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

$$452 \quad \text{normalized secured agents} = 1 - \left(\frac{\text{unsecured agents}}{\text{influenced agents}} \right) \quad (8)$$

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

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

468 **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

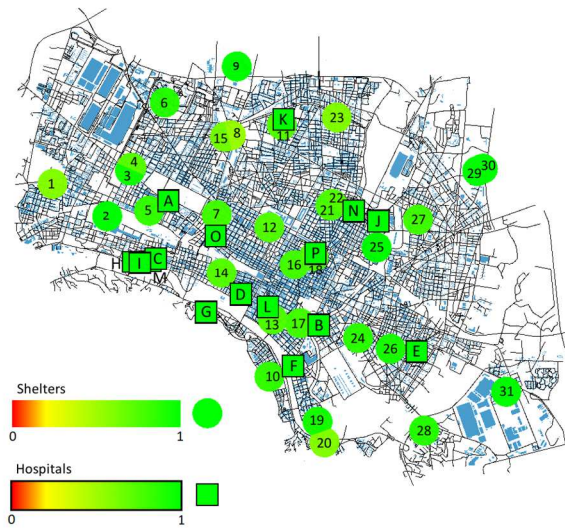
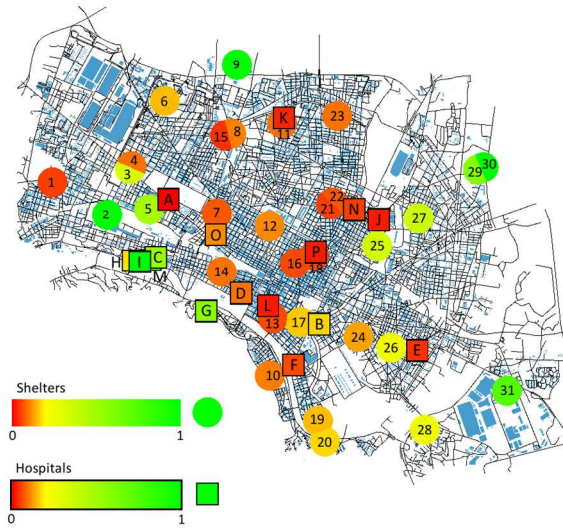
469

470 **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

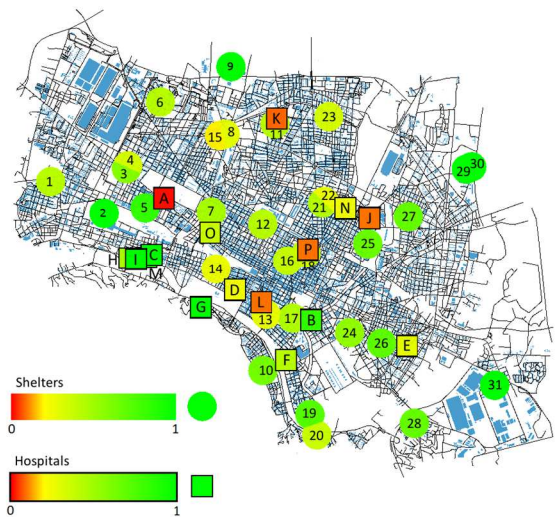
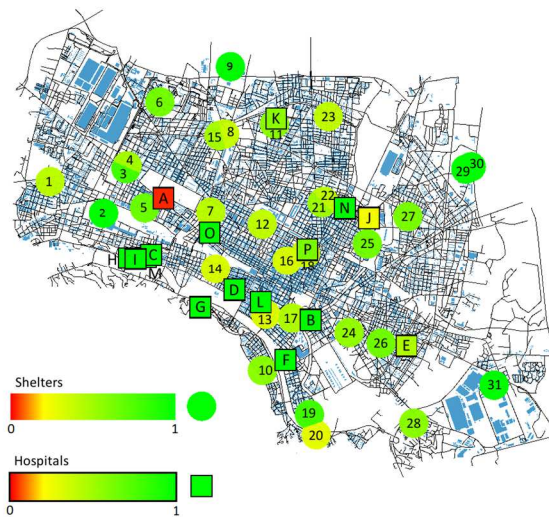
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472 Results of the simulations for Northridge and El Centro seismic scenarios are depicted in Figure 6.
473 Shelters and hospitals are marked through a color-graded scale as function of the number of secured
474 agents. This type of visualization allows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



(a)

(b)



(c)

(d)

482

483

484

485

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

488 **6 Concluding remarks**

489 A human behavior model is proposed in this paper that has been integrated into an agent-based model
 490 to simulate and study the evacuation process at the city scale. The panic behavior model considers
 491 the building damage level, the generated debris with the resulting interrupted roads, and the injured
 492 individuals. Furthermore, the human group behavior is implemented within the evacuation model to

493 consider its effect on the evacuation time together with the saturation of emergency facilities (i.e.,
494 shelters and hospitals). The model has been tested in a realistic urban environment, considering
495 several seismic scenarios and different combinations of panic conditions and group behaviors.
496 The negative impact of the panic condition on the evacuation process has been clearly observed, while
497 collective behavior, although not facilitating the evacuation process, does have a lower influence.
498 However, our model only considers static groups formed when agents leave a building. To further
499 study the phenomenon, future works could consider larger (>4) and dynamic groups merging and/or
500 disbanding during the evacuation process. Also, all the agents move on foot in our study, so
501 movement with vehicles could be a worthy inclusion in future studies. Indeed, during the evacuation
502 process, the panic level speeds up the actual velocity of pedestrians. However, the agents make blind
503 and irrational actions before reaching their destination increasing the evacuation process (*faster-is-*
504 *slower* phenomena). In all scenarios, the occupation of hospitals and emergency shelters is slow for
505 panic-cases compared to the non-panic case.
506 The saturation index of the emergency facilities has been estimated by considering their capacity,
507 vulnerability, and density. It can support decision-makers in the implementation and prioritization of
508 specific interventions to improve community resilience. Future works will be oriented to validate the
509 model through different real environments beyond the adopted virtual city and seismic scenarios.

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