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Simulating Earthquake Evacuation Using Human Behavior Models

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SUMMARY

In classical earthquake risk assessment the human behavior is actually not take into account in risk assessment. Agent-based modeling is a simulation technique that has been applied recently in several fields,such as emergency evacuation. The paper is proposing a methodology that includes in agent-based models the human behavior, considering the anxiety effects generated by the crowd and their influence on the evacuation delays. The proposed model is able to take into account the interdependency between the earthquake evacuation process and the corresponding damage of structural and non-structural components which is expressed in term of fragility curves. The software REPAST HPC has been used to implement the model and as case study the earthquake evacuation by a mall located in Oakland has been used. The human behavior model has been calibrated through a survey using a miscellaneous sample from different countries. The model can be used to test future scenarios and help local authorities in situations where the human behavior plays a key role.

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KEY WORDS: Resilience; Agent-based modeling; Damage scenarios; Panic model; Human Behavior model; Earthquakes; Evacuation model

1. INTRODUCTION

According to Max Roser (2016) the yearly average of deaths caused by natural disasters in the last decade is 94,136 [1]. Although the survival of people is mainly related to the resilience of buildings and communities [2], the human behavior after an extreme event also influences the number of fatalities. In this context, Agent-based models (ABMs) are a modern and powerful tool for testing the collective effects of individual action selection, helping local authorities to develop their risk management policies. ABMs have been applied in Civil Engineering mainly to simulate building evacuation. Indeed, most of the examples in literature focus on increasing the reliability of the agent models without taking into account the effects that structural/non-structural damage generated by fires, explosions or earthquakes can have on building evacuation.

The objective of this research is modeling the interdependency between the building evacuation process and the corresponding structural/non-structural damage, while taking into account also the influence of the human behavior [3]. In particular the research combines together both structural response analyses and corresponding earthquake damages with ABM simulations, human behavior and panic models. The methodology has been applied to a three-story building located in Oakland (CA) which has been base isolated using Friction Pendulum bearings and subjected to an earthquake

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[4]. The structural analyses has been performed with a software called OpenSees [5], while the earthquake losses have been evaluated using a Performance Assessment Calculation Tool (PACT) developed by FEMA [6]. The platform adopted for the ABM simulations is *RePast HPC* a software tool by Argonne National Laboratory [7] and since the models require high computational performances, parallel computing is used for simulating the earthquake evacuation. The *human behavior model* has been created developing a simplified version of the Extended *Belief*, *Desires* and *Intentions* (BDI) framework [8]. It has been calibrated using a survey that collected large data both in Italy and USA. The questionnaire design involved social desirability bias mitigation tools, according to Ajzen's Theory of Planned Behavior [9]. The *panic model* has been specifically designed for building evacuation after earthquakes and it includes three parameters: (i) the view of the emergency exit, (ii) the evacuation time and (iii) the density of the occupants. The parameters have been calibrated using the experimental results of a series of shaking table tests [10] [11] where the correlation between the structural analyses results and people's anxiety levels is determined.

2. DEFINITION OF AGENT-BASED MODELS

Agent-based models (ABMs) are computational models used to test the collective effects of individual action selection. In general, ABM allows the examination of macro-level effects from micro-level behavior. In agent-based modeling, a system is modeled as a collection of autonomous decision-making entities called *agents*. Each agent individually assesses its situation and makes decisions on the basis of a set of rules. An agent can interact with other agents, it is flexible and has the ability to learn and to adapt his behaviors based on the experiences. The definition of *agent* may represent individuals, groups, companies and so on. The models of their behavior and the reciprocal interactions are formalized by equations, but it is easily possible to consider individual variations in the behavioral rules and random influences or variations. Thus, ABMs can be combined with other simulation methods used in natural and engineering sciences, including statistical physics, biology and cybernetics.

ABM is used in a vast range of fields like biology, economy, ecology, social science, earth science, network theory, technology and also civil engineering. In ABMs, the components and the environment in which they exist are both modeled to observe if the overall system behavior of the model matches the behavior of the target (or subject) system. The benefits of ABM over other modeling techniques can be captured in three statements [12]: (i) ABM captures emergent phenomena that are the result of the interaction among the agents. (ii) ABM provides a natural description of a system. In many cases, ABM is most natural for describing and simulating a system composed of "behavioral" entities. Whether one is attempting to describe a traffic jam, the stock market, voters, or how an organization works, ABM makes the model seem closer to reality. (iii) ABM is flexible: The flexibility of ABM can be observed along multiple dimensions (e.g. it is easy to add more agents to an ABM). ABM also provides a natural framework for tuning the complexity of the agents: *behavior, degree of rationality, ability to learn and evolve, and rules of interactions*. Another dimension of flexibility is the ability to change levels of description and aggregation. One can easily play with aggregate agents, subgroups of agents, and single agents, with different levels of description coexisting in a given model.

2.1. *State of Art on evacuation using ABMs*

Several works can be found in literature in recent years related to building evacuation models using ABMs. These simulations can be used by designers and legislators to verify the level of safety of a structure and if the occupants would be able to evacuate during an emergency. The most reliable way to determine structure evacuation can be done experimentally on site, but in many cases these tests on site cannot be performed for all infrastructures. For example, if the administration wants to run an evacuation from an airport terminal, the economic losses due to flight and passengers delays would be too high and unfeasible [13]. In these cases, the best way to simulate an evacuation is to run an agent-based model on a computer.

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One of the earliest agent-based models is the segregation model by Thomas Schelling, from Harvard University [14] which has been discussed in his paper "Dynamic Models of Segregation" [15]. Even if he did not consider the use of computers, his models embodied the basic concept of agent-based models as autonomous agents interacting in a shared environment that gave a singular and aggregate result. Modern ABMs have been created by Axelrod in 1981, with his evolutionary simulations of cooperative behavior [16] [17]. Later in the '90s, with the appearance of softwares like StarLogo, Swarm, NetLogo, RePast, AnyLogic and GAMA, ABM started to be applied in several fields, such as social sciences. ABM began to focus on issues like designing effective teams, understanding the communication required for organizational effectiveness and the behavior of social networks. Later Bonabeau [12] has described very well the potential of modern ABM simulations, while Sun has developed agent-based simulations on models of human cognition, known as "cognitive social simulation" [18]. Recently ABM simulations have been used in several fields of civil engineering: from the building energy assessment to the simulation of terrorist attacks during a public event. For example, an interesting study in the field of building energy assessment is the one by Lee [19]. In his work he has simulated the interaction of people with the energy performances of a building, combining the results of the software EnergyPlus with the results of an ABM model developed in MATLAB where the behavior of each agent is controlled by few equation that give priority to the thermal comfort.

In literature can be found several application of ABMs to simulate evacuation at different spatial scales. For example, Chen [20] applied ABMs to simulate the evacuation of an entire town. This study uses an agent-based technique to model traffic flows at the level of individual vehicles and investigates the collective behaviors of evacuating vehicles.

Yin [21] created an agent-based travel demand model for hurricane evacuation simulation, which is capable of generating comprehensive household activity-travel plans. The system implements econometric and statistical models that represent the travel and decision-making behavior throughout the evacuation process. Zia [22] created a large dynamic simulation on a medium size European city. They created a Cellular Automata (CA) grid from a raster image of a city (CA definition is given in the following paragraphs). Then they modeled the city and the human behavior in Repast-HPC and they printed the results on raster images that were scaled to the resolution of the CA grid. Perkins [23] developed an ABM to simulate the reduction of the dwell time in the train stations, identifying as key parameters the number of train doors and their width.

Tang [24] created an agent-based model of a building subjected to fire evacuation. They used a fire dynamics simulator (FDS) based on the computational fluid dynamics and a geographic information system software (GIS) combined with an ABM application to model the occupants' response. In their case study, they simulate the coexistence and interaction between occupants, building geometry and fire effects. Later Dai [25] used the ABM to simulate the evacuation of the Georgia Dome (Atlanta, GA) to evaluate the stadium evacuation time and the dimensions of the crowding areas. The group behavior during the evacuation is also modeled, together with the size and the location of the bottlenecks. Tsai [13] simulated the evacuation due to multiple explosive devices (IEDs) at the Los Angeles International Airport (LAX). An important starting point of that simulation was that in airports there are not only business people (like in a train station during a work day), but also a large number of families. Households present a completely different model of human behavior, as they no longer follow the often assumed "self preservation" edict and often seek to ensure the safety of family members first.

2.2. State of Art on crowd behavior

There are different methods to classify the crowd behavior. For example, Gwynne [26] has studied the *crowd behavior* during fire emergencies and divided ABM applications in civil engineering in three categories:

1. optimization models
2. simulation models
3. risk assessment models

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Optimization models are created to optimize the position of all the emergency furnitures. Thus in these models the human behavior is not defined and the evacuees are considered like a uniform flow.

Simulation models considers all the aspects of the human behavior during an evacuation, including feelings and actions that are not strictly related to the evacuation process. These models allow designers to simulate, for example, how people use the emergency exits, the crowd formation and the evacuation time during a specific damage scenario.

Risk assessment models attempt to identify the hazards associated with the evacuation resulting from a fire or related incident and attempt to quantify risk. By performing many repeated runs, statistically significant variations associated with changes to the compartment designs or fire protection measures can be assessed.

According to Tsai [27], the *crowd simulations* can be also classified as "macro-oriented" and "micro-oriented". *Macro-oriented simulations* have been used in the past because of the computational constraints that previously prohibited a fine-grained treatment of simulations. In this type of simulations related to evacuation problems, the agent always knows where the nearest exit is and proceeds to it without hesitation. However, in real life, the police officer's duty is to direct lost people to the most appropriate exit, which is not always the nearest one. Not capturing this aspect of human behavior makes the simulation inaccurate and less useful for training purposes. *Micro-oriented simulations* model the simultaneous interactions of multiple agents, recreating the appearance of complex phenomena. Micro-oriented, agent-based simulations enable the representation of individual idiosyncrasies and realistically model evacuation scenarios. Raney [28] created an ABM simulation of the Swiss transportation system combining micro and macro scale simulations. From a micro-scale point of view, they considered an *agent* as a traveler with his own behavior, his strategic plan and his own long-term goals. From the macro-scale point of view the agents are approximated as particles in a fluid dynamics flow. Recently *crowd simulations* have been also used for designing evacuation plans in urban environments using modern softwares (e.g. TRANSIMS [29]).

2.3. *Multi-Agent Systems using High Performance Computing*

Multi-Agent Systems (MAS) are a promising technology which can be used to simulate large-scale distributed and complex systems [30] with several distributed nodes which necessitates High Performance Computing (HPC). HPC systems are based on hardware architectures with a large number of processors that work in parallel. The difficulty in designing the HPC simulations consists in selecting the proper instruction sequences and memory usage in order to avoid bottlenecks during the flow of calculations. In MAS applications, multiple agents are running on several computational nodes, so the parallelization of the code consists sharing several layers of data between the environment and the agents. Several applications of MAS systems using HPC technologies instead of the traditional Cellular Automata approach are available in literature. For example Quinn [31] has modeled the Terminal 1 of O'Hare International Airport in Chicago. He wrote the code in C with calls to the Message Passing Interface (MPI) library which is the most popular message-passing standard library for parallel programming. The *passengers* have been modeled using the *Social Forces Model* which is a model for only pedestrian movement. Similarly an important milestone in crowd simulations is achieved by Yilmaz [32] who has simulated the crowd of more than a million people during a marathon in Istanbul. In their parallel code they included all the objects of urban architecture and the agents which were distinguished between runners and public. The simulation code has been written in C++ and ran on NVIDIA CUDA GPUs, while the numerical results have been represented in a 3D environment. Recently more ABM softwares have added an HPC tool, such as NetLogo [33], which can be parallelized by R through a toolkit, and Repast [7], which has released a new edition for HPC simulation.

3. MODELING HUMAN BEHAVIOR

In an Agent-Based model, the agents' behavior is defined through three models:

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1. Human behavior (modeling their choices)
2. Crowd behavior (modeling their physical interaction)
3. State model (modeling their function in the community)

The human behavior in this research has been modeled using the modified version of the Belief, Desires and Intentions framework (BDI) [8]. The adopted framework is a simplification of the model proposed by Lee [34]:

$$P\left(t+h\right) = S \cdot P\left(t\right) + T \cdot W\left(t+h\right) \tag{1}$$

where $P(t) = [P_1(t), P_2(t), ..., P_n(t)]$ is an n-element vector that represents the preference state; $P_i(t)$ is the probability corresponding to option i at time t while h is the time step; S is the stability matrix, which represents the memory effect of the preference from the previous state in the diagonal elements, and the effect of interactions among the options in the off-diagonal elements; W is the weight vector of the n-element vector, where n is the number of attributes. $W(t+h)$ values are randomly chosen from a preference interval that is calibrated through a survey and T is a matrix that contrasts M. Its calculation is done before the beginning of the simulation by using the average values of the W vectors.
However, in panic situations the human brain does not work as previously described, but an *instinct mode* is activated. The history path, the long-term and the short-term memory do not influence the impulsive decisions that a person in panic can have. In these cases, after having defined the probability of each action through the Belief Module results, the actions will be chosen randomly (according to the probability patterns just defined).

3.1. A new method to model anxiety under emergency

As mentioned in the previous paragraph, the *instinct mode* is referred to the situation in which the agent is in panic and as a consequence specific feelings occur. The proposed model takes also into account three perceptions: (i) agent's estimation of evacuation time, (ii) density of agents and (iii) view of the emergency exit. These perceptions have been modeled starting from the definition of a Confidence Index proposed by Lee [34] and Li [35] where they used exponential functions for each panic component. The two models have been combined in a new equation as follow:

$$CI_t = (1-\alpha)\left[\beta e^{-\gamma\frac{t}{\bar{t}}} + \left(\frac{1-\beta}{2}\right)e^{-d_t} + \left(\frac{1-\beta}{2}\right)e^{-\gamma\frac{\rho}{\bar{\rho}}}\right] + \alpha CI_{t-1} \tag{2}$$

where α is a memory coefficient ($0 \leq \alpha \leq 1$) that describes how much memory is used in your decision. If α is equal 0, the person are not using any memory and his decision is made based on an impulsive behavior. On the contrary if α is equal 1, the decision is totally rational without any impulsive behavior; $d_t > 0$ is a coefficient that describes if the agent can or cannot see the emergency exit and its starting value is calibrated using the average evacuation time; t is the actual value of time, $\bar{t}$ is the evacuation time of the undamaged structure; $\beta \geq 0$ describes the influence of the perception of the evacuation time in an agent during the simulation. Its expression is given by:

$$\beta = \frac{t}{\bar{t}} e^{-\gamma\frac{t}{\bar{t}}} \tag{3}$$

In the case study analyzed the value of $\alpha = 0.6$ has been selected based on literature [34]; $\bar{t}$ is defined as the time when 80% of evacuees have left the building, p is the density of other agents around the targeted one, while $\overline{p}$ is the upper threshold of people density. If the density of people p is higher than $\overline{p}$, the person will be in panic ($\overline{p}$ is set equal to 3 people/m^2 in the case study), $CI_{t=0} \leq 1$ is calibrated through the results of a shaking table test. In the case study it is assumed that the evacuation time is not dependent on the first part of the evacuation process. The coefficient γ is set equal to 1.08, to have $e^{-\gamma}$ equal to 0.34, that is close to the weight at $\bar{t}$ (0.33) and to the panic threshold (0.35).

The starting value of the confidence index in the model has been calibrated using the data provided by Takashi [11]. Recently He has performed several shaking table tests on persons and asked them

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to fill a survey about the degree of anxiety, correlating their answers with the frequency and the maximum speed of shaking. The results of the tests are linear functions that put in correlation the velocity with the anxiety level at fixed frequencies. The velocity time history responses have been extrapolated from the results of the structural analysis for each ground motion developing the corresponding velocity response spectrum. Then both velocities and frequencies have been used to define Takashi anxiety levels for each ground motion and for each floor according to the results of their experimental tests. For each floor, the anxiety result is the 90th percentile of the 16 records considered in the analyses. While Takashi's anxiety level ranges between 0 and 4, in this paper it has been scaled proportionally in order to have a CI that ranges between 1 and 0 remembering that the CI is inverse proportional with respect to the anxiety level. From the analysis the resulting anxiety level is 0.33 for each floor, while the corresponding CI is 0.9175, so its starting value has been set to 0.9. Even if the CI seems high ($0 =$ extreme panic and $1 =$relaxed situation), the value is acceptable because the building is base isolated, so the movements are smoother and consequently the anxiety level is reduced.

3.2. *Crowd behavior model*

The interaction among agents is considered using a *crowd behavior model*. In this research it has been used the modified version of the Maze Routing Algorithm, also called Lee's Algorithm [36]. The method is based on the Breadth-First-Search (BFS) technique, that permits to find the shortest path between two points in a 2-D matrix. The matrix is a grid that represents all the environment, including the obstacles. The algorithm has been modified by the authors to take into account the presence of the crowd, so if the agent cannot move in an adjacent cell because of the presence of another agent, the process is repeated until a new path is determined to avoid the obstacle. In normal condition an agent moves with the speed of 1.2 m/s, if they are not seriously injured they move at the speed of 0.6 m/s, while if seriously injured, they don't move at all, until they are rescued by another agent. At each time step of the simulation, the agent collects information for his decision making process from the external environment and from the mental elaboration data (e.g the agent can recognize the presence of the emergency exit, a member of his family, a group of people, an injured person and his own level of injury).

4. CASE STUDY: 3-STORY BUILDING IN THE BAY AREA

The case study used in the analysis is a 3-story steel office building. The lateral force resisting system is a special moment resisting frame (SMRF) that is designed according to ASCE7-05 for Los Angeles sites. Its dimensions are $180' \times 120'$ ft)(54.9×36.6 m) in plan , equal spans of 30'-0" (914 cm) between columns and equal story heights of 15'-0" (457 cm). The structure has been designed as an office building, but at the ground floor there is a supermarket and five small shops.

4.1. *Numerical Analysis Model*

Nonlinear time history analysis is used to obtain the structural response using different ground motion intensities. The numerical simulations in the study are conducted using OpenSEES [37]. The superstructure in the analyses is a three story moment resisting frame, while the base isolation system is composed of single friction pendulum bearings (SFPB). The structure elevation scheme is shown in Figure 1. The building has been originally designed to be located in Los Angeles, however the member sizes have been redesigned according to the new hazard level in Oakland with a force reduction factor of 8 which is required in code regulation ASCE 7-10 [38] for a SMRF and story drift ratio limit under design level seismic event as 2.5%. The member sizes of beams and columns are summarized in Table I. For the base isolated case, the intermediate moment resisting frame (IMRF) are used for the superstructure. The member sizes for base isolated intermediate moment resisting frame (BI-IMRF0 are also summarized in Table I.

A distributed plasticity model is used for the elements of the superstructure. For the beams and the columns, the force based beam-column elements [39] are used. A fiber-based section is used to take

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Floor Element	Column	Beam
Base	NA	W24x68
First Story	W14x145	W24x68
Second Story	W14x145	W24x62
Third Story	W14x90	W18x46

Table I. Summary of member sizes selected for the BI-IMRF design

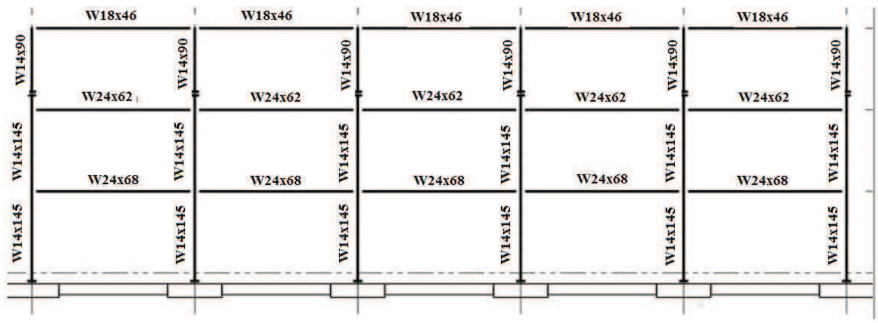

Figure 1. Prototype SMRF elevation scheme

into account for the interaction of axial force and bending moment, although, the axial force in the beams may be small. The sections considered for the beams and the columns are W flange sections which are built by putting together three rectangular fiber patches. $Steel02$ material in OpenSEES is used for the beam and column sections with a yielding stress of 50 ksi and an hardening ratio of 0.3%. The number of integration points along each element is three. Since it is a 2-D analysis, only in plane bending is considered and only one fiber is used for each layer along the out of plane direction. The total number of fibers and integration points are selected based on a parametric study. The moment resisting frames are modeled using fiber based beam column elements with spread plasticity which neglect the material deterioration. The P-delta effects are considered in the model. Since in the 2-D analysis model it is considered only the lateral force resisting system of the entire building, the gravity loads added in the numerical model only consider the loads acting on the perimeter. However, in reality the gravity loads acting on the interior columns will also contribute to the nonlinear geometric stiffness. In order to capture these additional P-delta effects induced by the internal gravity columns which are not modeled in the 2-D model, leaning columns are connected to the lateral resisting frame and loaded with the gravity load acting on all the internal columns. The panel zone has been modeled as a rigid element with a size that corresponds to the beam width and column height respectively. It is assumed 10 times stiffer than the elastic elements which are connected directly to the end part of the rigid zone. The fundamental period of the structure is 1.3 secs. The bearing used in the case study is Single Friction Pendulum Bearing (SFPB) [40] with a friction coefficient equals to 10% and a radius equal to 88 inches. The effective period of the isolation system under the design displacement level demand is around 2.5 secs. The bearing weight is assumed to be constant in the simplified model, so the change of vertical force on the bearing will not influence its horizontal behavior. The 2-D model in OpenSEES is not including the vertical ground motion, but only captures the horizontal force-displacement behavior of the bearing (Figure 2). The displacement capacity of the bearing is selected based on the median of the Maximum Credible Earthquake (MCE) event, which has 2% probability in 50 years. Generally, to protect the bearing and prevent it from failure, a moat wall is built around the isolation plane, so it can protect the bearing from exceeding the displacement capacity. The size of the seismic gap is selected based on the median MCE level displacement demand which is 68.58 cm (27 inches) in this case. A rigid stop is used to simulate the impact on the moat wall. In detail, when the displacement of the bearing is exceeding the median MCE displacement demand, the model provides a large stiffness to mimic

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a sudden stop at the base, but it does not consider the energy dissipation due to the crash of concrete and the local damage during the impact.

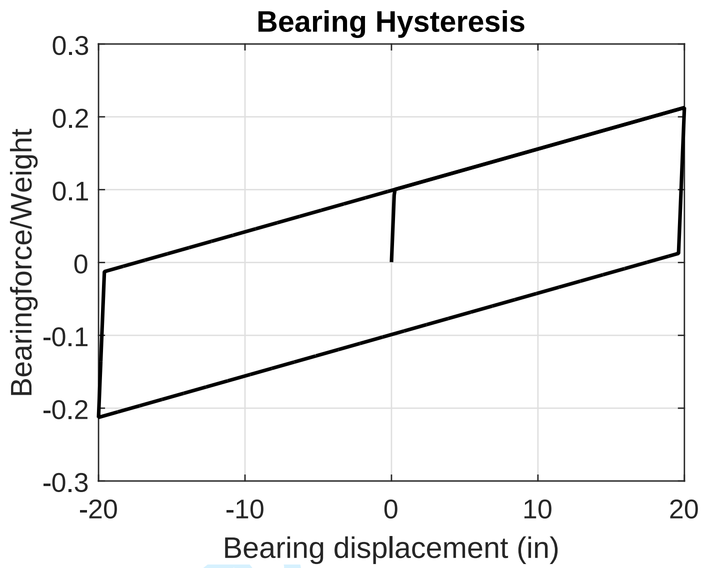

Figure 2. Bearing Hysteresis modelled in OpenSEES

4.2. *Ground Motion Selection*

The building is located in Oakland, California where the site class is C/D, while the $V_{s30} = 360m/s$ [41]. The incremental dynamic analysis (IDA) is performed using 16 ground motions with different scale factors. The ground motion set has been selected based on the target spectrum of 2% 50 yrs uniform hazard spectrum for the Oakland site. The selected 16 response spectra with 5% damping are compared with the target spectrum and shown in Figure 3.

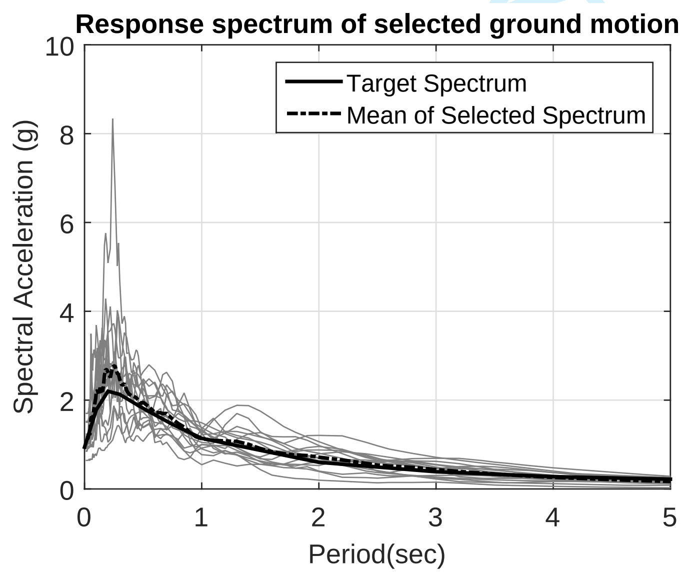

Figure 3. Selected ground motions used in the analysis corresponding to 2% probability of exceedance in 50 years

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The scale factors used for the IDA and the corresponding spectral accelerations at the fundamental period of the fixed base structure and the fundamental effective period of the isolated structure are summarized in Table II.

GM Scale Factors	Sa (Tm=2.5 sec)	Sa (Tm=1.3 sec)
0.3	0.15	0.27
0.4	0.20	0.36
0.5	0.25	0.45
0.6	0.30	0.54
0.7	0.35	0.63
0.8	0.40	0.72
0.9	0.45	0.81
1.0	0.50	0.90
1.1	0.55	0.99
1.2	0.60	1.08

Table II. Scale factors for the corresponding spectral acceleration values of the base isolated and of the fixed base structure

The results of IDA in term of interstory drifts at the different story levels are shown in Table III.

	Fixed-base		Base-isolation	
Story	Max	Min	Max	Min
1	15.2	2.1	9.5	0.8
2	15.7	2.3	9.4	1.1
3	15.5	3.7	9.9	3.2

Table III. Inter-story drifts [%] at MCE corresponding to 2% probability of exceedance in 50 years

The results summarized in Table II and Table III for each step of IDA and for each ground motion have been used as input in PACT - *Performance Assessment Calculation Tool*, a software created by the Federal Emergency Management Agency [42] [43].

4.3. *Modeling earthquake damage*

The software PACT has been used for defining the percentages of damaged components and injured people. The damage assessment in each component is evaluated using fragility functions. Each nonstructural component have been specified and Table IV reports the percentages of damaged components at the different story levels.

Component Type	Ground	First	Second
Suspended Ceiling	47.6	42.6	78.8
Office Work Stations	80.0	48.1	44.4
Objects on Shelves	88.3	86.8	76.3
Desktop Electronics	93.3	90.0	91.7
Objects on Racks	93.3	100.0	80.0

Table IV. Total percentage of damaged non structural components

All the nonstructural components, piping systems and other installations have been analyzed. Most of them reported minor damages that did not interfere with the movement of the agents, so they have not been included in Table IV. The results in Table IV and V correspond to the mean

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values of the 16 time histories corresponding to the MCE case, scale factor, r=1. In PACT it is possible to define the population models and the corresponding densities for each floor. The chosen quantity for retail areas is 0.2 agents/m^2, which means approximately 20 agents/1000 ft^2, therefore the number of agents in crowded hours in the ground floor is equal to 380. The people density in the office areas is 0.1 agents/m^2, which means approximately 10 agents/1000 ft^2, therefore the peak value of agents in the first and second floor is 185. Since PACT reports the total value of injured people, the research assumes that 30% of people are seriously injured (Table V).

Floor	Slightly Injured [%]	Seriously Injured [%]
1	6.1	2.6
2	3.2	1.4
3	6.7	2.9

Table V. Total percentages of injured people by floor level

4.4. Calibrating the human behavior using questionnaire

The probabilities to perform specific actions have been defined through a questionnaire, that has been developed according to the suggestions given by Ajzen's Theory of Planned Behavior (TPB) [9]. The core of Ajzen's theory is the individual's intention to perform a given behavior: intentions are assumed to capture motivational factors that influence a behavior. An important postulate of his theory is that "*behavior is a function of salient information, or beliefs, relevant to the behavior*" [9]. People can perceive a large number of perceptions simultaneously, but only few of them are considered instantaneously. So, when modeling the human behavior, only the main perceptions should be considered. In this work, eight typologies of agents are defined according to the following properties: the agent can be alone or in group (with his family/friends), he can be injured or not and he can see the emergency exit or not. According to their typologies and feelings, the agents are able to perform the following actions: (i) help a person which can be either moderate or seriously injured, (ii) follow a group that is running towards a different direction and (iii) looking for a missing relative/friend. The results of the questionnaire that is used to calibrate the human behavior model can be affected by errors due to biased answers,so the form has been created according to modern TPB's. For example, when people answer to a survey, they tend to distort their answers in order to appear nice persons in a specific situation [44]. This phenomenon leads to a disruptive error in social sciences models and it is called "*social desirability bias*". Sometime this bias can be avoided using indirect questions, but during an evacuation it can generate other type of bias. In the proposed questionnaire sex, job and age of the responder is asked, but the key question is: "*will you help an injured person?*" Since in this specific case indirect questions are not applicable, in order to reduce the *social desirability bias* one option is to transfer to the people a real sensation of the emergency environment through images and videos (to be seen before filling the form) and provide a questionnaire with multiple answers. In this specific case 5 choices are provided: *"Yes", "Probably yes", "I don't know", "Maybe no"* and *"No"*. Each question is introduced with a brief phrase and a sketch describing the psychological context that the agent should be subject to. The probability of helping a person (moderate or seriously injured) is chosen from a probability interval that is created by people who answered "Yes" and people who answered "Yes" and "Maybe yes". The probability of following a group of people is chosen from a probability interval that is created by people who answered "Yes" and "Maybe yes" and people who answered "Yes", "Maybe yes" and "I don't know". The probability of looking for a missing relative or friend is chosen from a probability interval that is created by people who answered "Yes" and "Maybe yes" and people who answered "Yes", "Maybe yes" and "I don't know". The survey has been created through an online GoogleForm, that allows to organize the answers in real time and in an ordered and manageable way. The questionnaire has been translated both in Italian and in English and has been advertised through social networks and mailing lists. A sample of the questionnaire is reported below.

During the evacuation, you are with YOUR FAMILY or with your friends. Fortunately, you are not injured, so you can walk and run and you are able to see and hear well the most important things of the environment, even if there is crowd and smoke. Fortunately you see the emergency exit!

You are EVACUATING the building, but... DAMN! You can not find a member of your family/friends!!! What will you do?

1. *I will come back and look for the missing person.*
2. *MaybeI will come back and look for the missing person.*
3. *I don't know.*
4. *Maybe I will continue the evacuation: paramedics are more experienced than me, they will give him a better help.*
5. *I will continue the evacuation: paramedics are more experienced than me, they will give him a better help.*

You see a group of people running in a different direction respect the emergency exit one. How likely will you follow them?

1. *I will follow them: maybe they know a better exit!*
2. *MaybeI will follow them: maybe they know a better exit!*
3. *I don't know.*
4. *Maybe I will not follow them: I will exit on my own through the emergency exit!*
5. *I will not follow them: I will exit on my own through the emergency exit!*

You find a not seriously injured person. How likely will you give him a help (or first aid)?

1. *I will help him.*
2. *Maybe I will help him.*
3. *I don't know.*

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4. *Maybe it's not necessary to help him: paramedics will arrive soon!*
5. *It's not necessary to help him: paramedics will arrive soon!*

You find a not seriously injured person. How likely will you give him a help (or first aid)?

1. *I will help him.*
2. *Maybe I will help him.*
3. *I don't know.*
4. *Maybe it's not necessary to help him: paramedics will arrive soon!*
5. *It's not necessary to help him: paramedics will arrive soon!*

The results of the survey are summarized in the matrices below. It is important to note that the non-diagonal elements of the matrices have been assumed equal to -0.01 in order not to have interaction among the probabilities of performing specific actions. $W_{low,5}$ and $W_{up,5}$ are the lower and upper vector limits for the W(t+h) definition. W_{avg} has been used for T_5 calibration.

$$S = \begin{bmatrix} 0.9 & -0.01 & -0.01 & -0.01 \\ -0.01 & 0.9 & -0.01 & -0.01 \\ -0.01 & -0.01 & 0.9 & -0.01 \\ -0.01 & -0.01 & -0.01 & 0.9 \end{bmatrix}$$

$$T_5 = \begin{bmatrix} 0.130 & -0.01 & -0.01 & -0.01 \\ -0.01 & 0.374 & -0.01 & -0.01 \\ -0.01 & -0.01 & 0.149 & -0.01 \\ -0.01 & -0.01 & -0.01 & 0.162 \end{bmatrix}$$

$$W_{low,5} = \begin{bmatrix} 0.965 \\ 0.147 \\ 0.545 \\ 0.483 \end{bmatrix}; W_{up,5} = \begin{bmatrix} 0.965 \\ 0.182 \\ 0.860 \\ 0.692 \end{bmatrix}; W_{avg,5} = \begin{bmatrix} 0.965 \\ 0.164 \\ 0.703 \\ 0.587 \end{bmatrix}$$

The survey has been filled by 543 responders who lives both in U.S.A. (California) and Italy, with different ages and nationalities, so the sample is very miscellaneous. In Figure 4 is shown the age distribution of the sample.

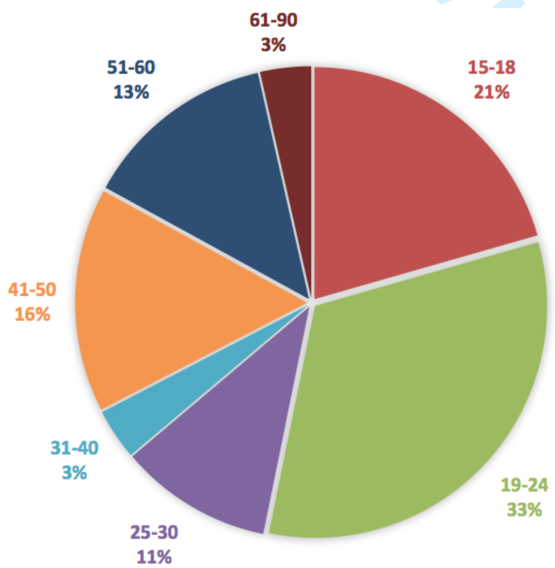

Figure 4. Age distribution of responders

The age distribution of the sample does not correspond to the percentages of a specific building or population, because the sample was selected randomly. However, additional data have been collected during the survey which will allow in the future to develop a human behavior model for a specific category of people (e.g. the behavior of a female student between 20 and 25 years old). The histogram in Figure 5 shows the probabilities to follow a group of people that is not moving in the agent's preferred direction.

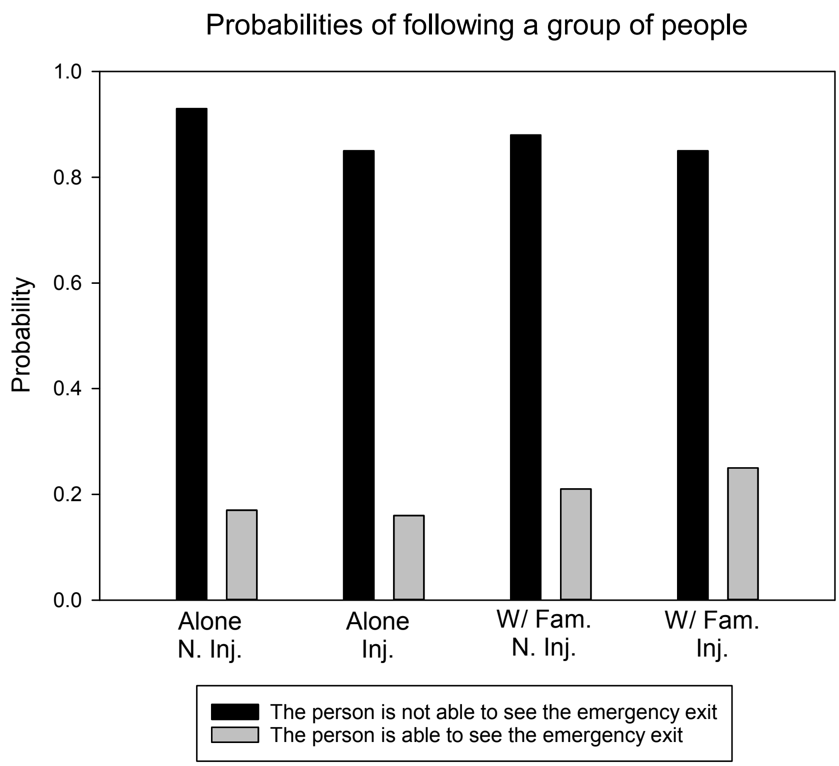

Figure 5. Probability of following a group of people.

From the analysis of the survey it is possible to make the following considerations. (i) Most of people tend to follow a group if they do not see the emergency exit. (ii) If an agent can see the emergency exit and he is not injured or he is with his family/friends, he tends to move toward the exit on his own. (iii) A larger number of people would follow a group if they are injured, but they see the emergency exit. This increment is about 5-10$\%$ with respect to a healthy person. The histogram in figure 6 reports the willingness to help an injured person, depending on the state and the feelings of the agent.

From the graph it appears that the willingness to help a person is extremely reduced if they are injured as expected.

5. NUMERICAL RESULTS

Agent-Based simulations have been performed using Repast HPC, a software tool for high-performance distributed computing platforms, written in C++ and using MPI (Message Passing Interface) libraries for parallel operations [33]. The agents have been set to move among cells $30 \times 30cm$ wide, that is the highest resolution in the simulation.

The CI has been calibrated using the evacuation time corresponding to the instant when 80$\%$ of agents are out of the building. First, the evacuation times have been determined using models that neglect the structural damage, the human behavior model and the panic model. The corresponding

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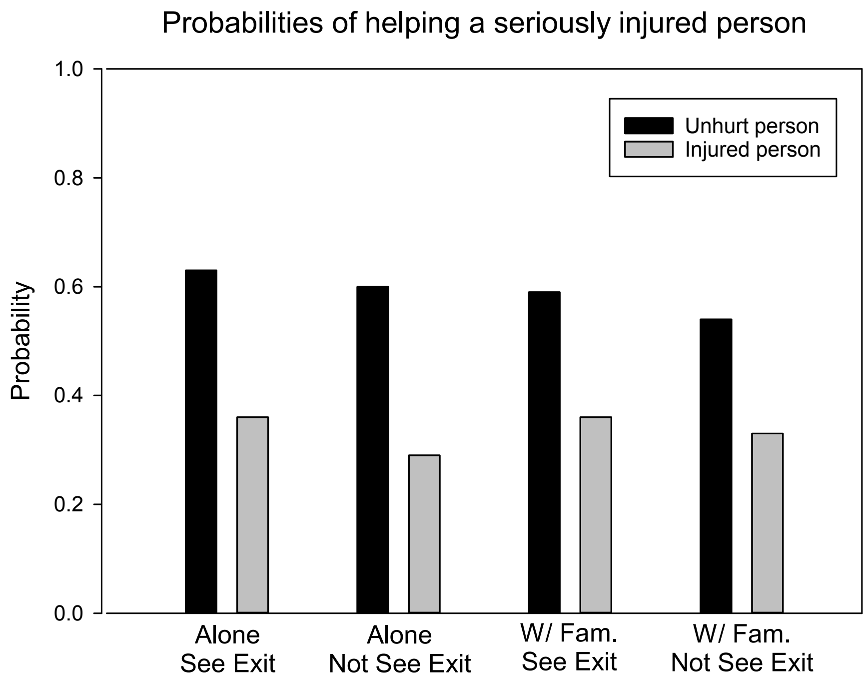

Figure 6. Probabilities of helping a seriously injured person

values grouped by floors are shown in Table VI where it is shown also the d_t dispersion in the calibration .

Floor	n° of persons	Evac. Time [s]	δ d_t
1	275	14.0	0.019
2	140	24.0	0.0054
3	140	49.0	0.0042

Table VI. values of evacuation times used to calibrate Equation 2

After the setup of all parameters, the numerical simulations have been performed. Figure 7 shows the plan view of the ground floor of the building in REPAST HPC. In red and orange are shown the nonstructural damages inside the building, which can be an obstacle for the agent during the evacuation.

Table VII reports the total evacuation times for each floor when the structural damage, the human behavior model and the panic model are included in the simulation. Figure 8 shows the two cumulative curves of the number of evacuated agents vs. time for both the left and right stair shown in Figure 7. It should be noted that the evacuation time depends on the intensity of the earthquake event, because if there is a relevant number of deaths or seriously injured persons, they will not start evacuating until the first responders will rescue them. Obviously this condition will increase the evacuation time significantly.

Instead in Figure 9 are shown the cumulative curves with and without human behavior model.

The evacuation time (80th percentile) without the human behavior model is 14.0 seconds, while with the human behavior model is 25 seconds, assuming a normal distribution for each model. In Figure 10 it is shown the 80th percentile of evacuation time at the ground floor for different percentages of evacuees (20%, 40%, 60%, 80% and 100% of the overall amount of people).

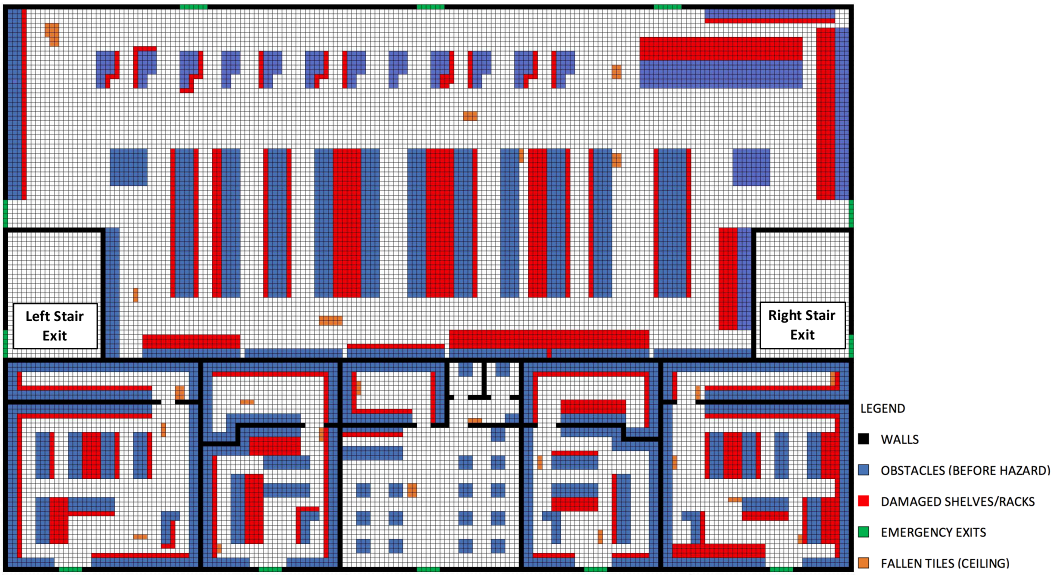

Figure 7. Case study: ground floor

Emergency Exits	n° of persons	Total Evac. Time [s]
First Floor Exits	380	35.0
Left Stair Exit	160	104.0
Right Stair Exit	210	118.0

Table VII. Evacuation Times

By observing the curves in Figure 10, it can be observed that the evacuation time remains constant even if the number of evacuees increases. This means that there are no bottlenecks or crowd in the building. The evacuation time increases if the human behavior model is activated, because in this case the agent interact each other and with the external environment.

6. CONCLUDING REMARKS

The paper is proposing a new human behavior model to be used during the simulation of building evacuation after earthquakes in agent-based models. The proposed model is using as input parameters the anxiety level, the crowd density and the view of the emergency exit. The interaction between the agents and the external environment damaged by the earthquake is also taken into account in the agent-based simulations. In particular the number of injured people and the obstacles caused by structural and nonstructural damaged components in the building are obtained by the output of a software called PACT and used as input of the agent-based simulations. The numerical results of the simulations show that the human behavior model and the panic model affect the results of the agent-based simulations. The inclusion of these models in the simulations

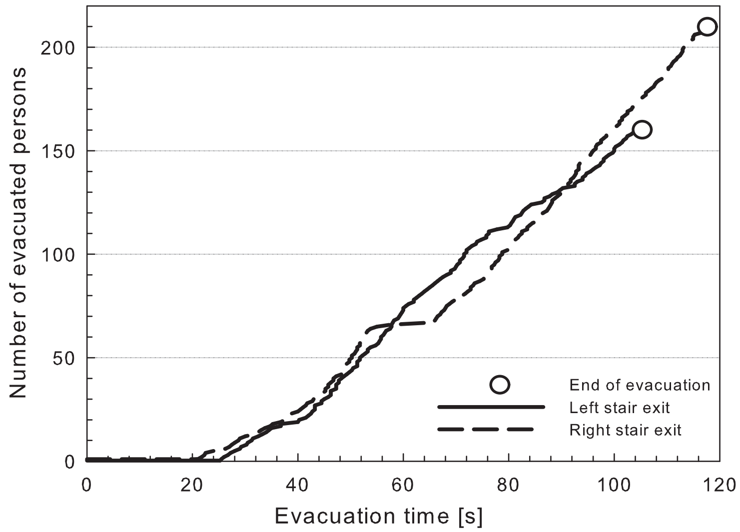

Figure 8. Number of evacuated persons vs. time

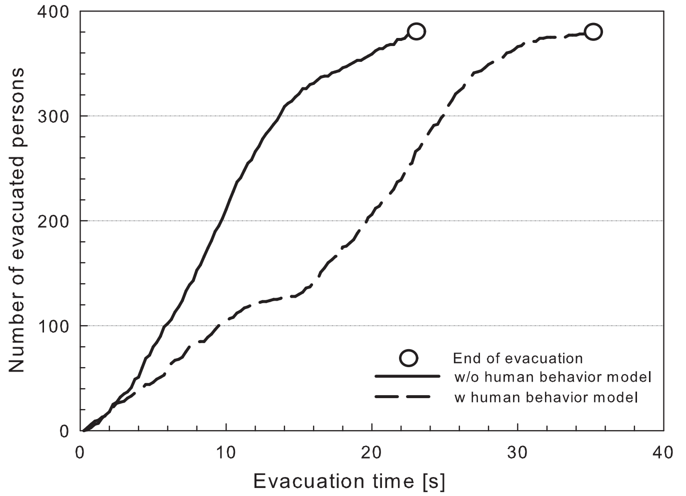

Figure 9. Comparison with and without human behavior model - 1^{st} Floor

will increase the computational time of the analyses, but if they are not considered, the evacuation time is usually underestimated. However, the higher computational demand in the simulation can be reduced through the use of parallel computing.

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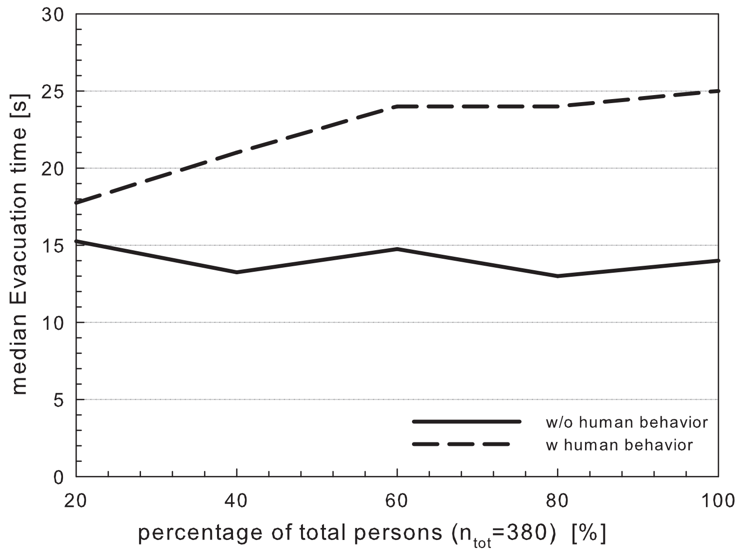

Figure 10. Sensitivity of the median evacuation time vs. crowd level

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