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A hierarchical agent-based approach to simulate a dynamic decision-making process of evacuees using reinforcement learning

Sajjad Hassanpour [a,b,*], Amir Abbas Rassafi [a], Vicente A. González [b], Jiamou Liu [c]

[a] Faculty of Engineering, Imam Khomeini International University, Qazvin, Iran
[b] Department of Civil and Environmental Engineering, The University of Auckland, Auckland, New Zealand
[c] Department of Computer Science, The University of Auckland, Auckland, New Zealand

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ABSTRACT

Simulation models are an undeniable tool to help researchers and designers forecast effects of definite policies regarding pedestrian social and collective movement behaviour. Considering both the environment's details and the complexity of human behaviour in choosing paths simultaneously is the main challenge in micro-simulation pedestrian dynamics models. This paper aims to present a novel comprehensive hierarchical agent-based simulation of pedestrian evacuation from a dynamic network of the environment using reinforcement learning, which is the closest to human behaviour among the other machine learning algorithms. In the approach, agents autonomously decide through a three-layer hierarchical model, including goal, node, and cell selection layers. A multinomial logit model is used to model the process of choosing the main movement direction at each time-step. The proposed model was successfully tested to simulate the pedestrian evacuation process from the Britomart Transport Centre platforms in Auckland during an abstract destructive event. Maximum evacuation flow, total evacuation time, average evacuation time, and average evacuation flow were investigated as dependent variables through different evacuation scenarios. The results from the approach can be used by designers and managers to optimise the quality of evacuation; also, the proposed model has the potential of becoming a potent tool for constructional management if coupled with other constructional tools.

1. Introduction and overview

Considering human behaviour is an undeniable parameter in today's design and management. However, predicting human behaviour has always been one of the most complex issues that scientists and researchers have ever confronted due to its inherent uncertainty. This complexity also arises from the simultaneous consideration of physical and psychological dimensions. Simulation of human behaviour is turning to a crucial necessity in public and social system design, such as designing airports or public transportation hubs. Knowing the human preferences to move toward a path or in a building becomes even more vital when considering especial situations like emergency evacuations due to a terrorist attack, fire, natural disasters, or other emergent incidents. Searching about human stampedes, we can find numerous examples of crowd catastrophes. Therefore, studying the evacuation performance is useful not only to optimise the space design of transportation infrastructure but also to reduce the loss of lives during emergency events.

* Corresponding author. Faculty of Engineering, Imam Khomeini International University, Qazvin, Iran.
E-mail addresses: s.hassanpour@auckland.ac.nz (S. Hassanpour), rasafi@ikiu.ac.ir (A.A. Rassafi), v.gonzalez@auckland.ac.nz (V.A. González), jiamou.liu@auckland.ac.nz (J. Liu).

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There are significant studies about the evacuation simulation; however, they still lack a comprehensive approach to address the details of the smart, dynamic decision-making process during movement through an environment in different conditions. This paper tries to present a novel hierarchical agent-based simulation framework for pedestrian evacuation, which combines artificial intelligence and choice models to reach a more realistic model of the human evacuation behaviour in a dynamic environment. It uses the utility-based discrete choice models and reinforcement learning for the first time to simulate human exploration during the evacuation process from a dynamic network of the environment under a destructive event. Combining the proposed approach with other specific tools can lead to a handy tool for constructional designers and managers. All the simulation codes and interfaces were specifically developed within the NetLogo 6.0.4 software environment (Wilensky 1999), which is a free multi-agent programmable modelling environment.

2. Literature review

Microscopic pedestrian simulation studies have been heavily concerned in pure physics, especially statistical physics for the last several years or decades. There are two main approaches where human movement details have been modelled in case of emergency and other scenarios: One is modelling relying on a continuous system that always refers to the set of kinetic equations. A representative concept is what-is-called 'social force model' where the interaction between agents as attracting and expelling forces, attracting force to a wall, following tendency to a leader and various specific situations (emergency guidance effect, for instance) can be considered (Helbing and Molnar, 1998). Another idea is so-called Cellular Automata (CA) model where space (domain) is discretised into cells, and each agent occupies one cell and moves to one of the neighbouring cells. Few studies have tried to combine these two approaches, like developing a cellular automaton model on social forces interaction in building evacuation (Chen et al., 2019). The proposed hierarchical agent-based model wisely integrates these two mentioned approaches to consider dynamic changes in both the environment and pedestrian social interaction.

Agent-based modelling (ABM) is a useful tool to derive the dynamic behaviour of a complex system from studying the individual agents who make up the system; in other words, it is a bottom-up procedure which allows the examination of macro-level effects from micro-level behaviour (Railsback and Grimm 2011). In these models, agents are fully autonomous entities who interact with the environment and other agents (Macal and North 2010). The ABM is often confused with CA due to their close core mathematical approach of simulation and application; however, the ABM is connected to information sciences and artificial intelligence, not just computer sciences (Gilbert 2007). In agent-based models, the interactions between agents play an important role. In this kind of simulation models, we deal with an environment that contains both objects and agents that are assumed as autonomous entities. By establishing some logical rules, all these entities are interacting with each other in this multi-agent system (Pluchino et al., 2014; Liu et al., 2016).

In recent years some studies are trying to combine different Computer-aided Design (CAD) software supporting BIM with ABMs in order to reach an appropriate approach to indicate human behaviour into the design and management. For instance, some studies used the combination of ABM with other constructional tools to present a model to test the usability of a building design before its construction due to prospective realistic occupants' behaviour and interaction (Andrews et al., 2011; Rossini et al., 2017).

Many studies are using ABM for evacuation process from different situations (Joo et al., 2013; Pluchino et al., 2014; Liu et al., 2016; Liang et al., 2016). Some have tried special environment situations such as invisibility (Cao et al., 2019). Also, some studies are trying to use coupling ABM with other constructional models in the evacuation context. The study of coupling BIM and behavioural models for analysing the evacuation time in different predefined scenarios by Cheng et al. is a good illustration (Cheng and Gan 2013). Mohamed Marzouk and Ismail Al Daour used BIM and agent-based evacuation simulation of labours as an input for a Multi-Criteria Decision Making process considering total project time, total cost and evacuation time to reach the best construction method scenario (Marzouk and Daour 2018). However, the details of human behaviour and the way agents think still were not adequately considered as they all used different rule-based ABMs.

While many studies are done around the evacuation from undamaged structures, Liu et al. combined nonlinear finite-element modelling, probabilistic modelling of damage, and ABM to analyse evacuees' dynamic behaviour in a damaged structure (Liu, C. Jacques et al., 2015). More details of behaviour were presented in this study by having more realistic assumptions and considering social interactions in the group movement of agents, but still, the deterministic rules do not consider the uncertainty originated from the psychological aspects of behaviour.

Consequently, a researcher tried to model the awareness and knowledge of human through the dynamic changes of the environment during the event of an evacuation (Tan et al., 2015). They presented an ABM simulation model considering the evacuee's knowledge which led to more realistic evacuation simulation in fire emergency scenarios.

Many studies have focused on modelling the agents' decision-making process, which is one of the main steps of the evacuation simulation (Gwynne and Hunt 2018; Marzouk and Mohamed 2019). For example, some utilized the affordance concept to incorporate psychological aspects of human in navigation process (Hassanpour and Rassafi, 2021; Joo et al., 2013). However, few of them utilised hierarchical structure which is one of the founding insights of the cognitive revolution (Botvinick 2008). Sehyun Tak et al. tried to develop a modified cell transmission model (CTM) to embed the concept of agents that can make decisions on their destinations and travel direction at every time step (Kim and Yeo, 2017). Few studies focused on the psychological behaviour in evacuation process using choice models where they used a mixed nested logit to model exit choice process (Haghani et al., 2015).

Cimellaro et al. tried to present a new behavioural model to simulate the evacuation after the earthquake. The anxiety level, the crowd density, and the view of the emergency exits are considered input parameters (Cimellaro et al., 2017). In their study, a questionnaire was used to capture the preferences to calibrate the human behaviour model after the earthquake instead of using some

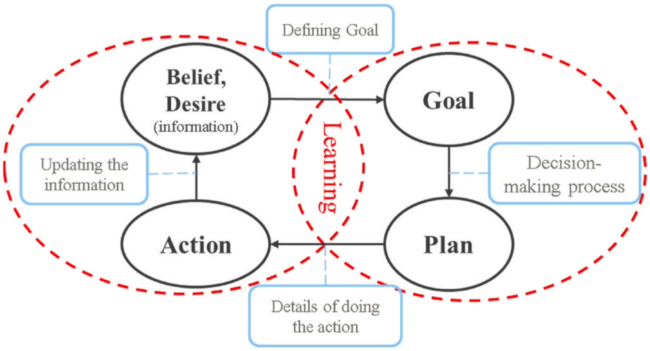


Fig. 1. The structure of BDI in the study.

presumptions.

With the surge of new technologies, the integration of automation and cognition into various engineering applications is a vital issue in recent decades. Accordingly, Artificial intelligence (AI) is used as a strong tool to help scientists in many fields, including evacuation studies (Wang, Shi et al., 2019). In a few studies, the q-learning method has been used for human exploration and interaction through a dynamic environment (Le et al., 2017).

Therefore, generally reviewing the literature concerning human behaviour in building design, three main challenges or considerations in the studies can be found: 1) considering an appropriate geospatial framework 2) considering the psychological and logical aspects of human behaviour 3) considering the dynamic interactions of agents. Therefore, studies due to their level (microscopic or macroscopic) focused on one or some limited aspects of the evacuation process. In the proposed approach, all the above-mentioned challenges are carefully contemplated by using a novel hierarchical framework. Coupling the graph-mode network and cellular approach enables considering the whole evacuation process in one package. It uses the integration of utility-based discrete choice models and Q-learning, for the first time, to simulate human exploration during the evacuation process from a dynamic network of the environment under a destructive event. Changes during an event dynamically will be an input into a new intelligent agent-based model using reinforcement learning for agents' exploration through the environment to consider more details of human thinking ability in the decision-making process. In this way, agents decide in a higher layer for their goals and in lower layers for the details of their movement.

3. Modelling approach

The main challenge in evacuation simulation models is considering the exploration process by an autonomous agent who is intelligently searching to find the best way to reach his/her object in a dynamic environment. Some people do not have enough information about the geometry of the network so they will start exploring to get as much information as they can to find their way out. On the other hand, some people know the best routes as they may already be familiar with the environment. Still, we shouldn't forget that in an emergency condition (e.g., fire or earthquake) some elements of the environment and the availability of paths may be affected by the destructive event; therefore even being familiar with the geometry of the network may not help as it is a "dynamic environment". By dynamic environment, we are addressing the non-structural changes and damages caused by a destructive event during the simulation period.

In the following section, first, we describe the basic framework of the hierarchical architecture in an agent's decision-making process, and then we discuss the details of physical simulation for both the environment and the agents. Then, the movements within an intelligent evacuation process are explained in detail. The whole model has been originally coded in NetLogo which is a specific platform for agent-based simulation models.

– *The main framework of hierarchical agent system architecture*

The belief-desire–intention (BDI) modelling is a known sequence for defining the agents' attitude and planning process in the simulation context. The agents initially find a belief set by observation and candidate their desirable goals. The goal selection stage leads to a planning stage where they construct their plan sets to achieve the selected goal. Finally, the chosen plans will trigger the actions. The whole procedure is similar to what automatically happens in humans' mind when deciding and doing different actions. Although the core concepts of the BDI framework is based in folk psychology which can be easily understood by people, many generic aspects of human behaviour and reasoning are not captured in the framework (Norling 2004).

To have a more realistic evacuation phenomenon of an autonomous agent who can experience and learn, we used hierarchical artificial intelligence within the BDI framework. Fig. 1 shows the overall structure of the BDI used in this study where the agents have the ability to learn and remember their experiences while selecting their goals and plans. The hierarchical structure in human behaviour has been a revolutionary finding in the computational cognitive intelligent models (Botvinick 2008). Therefore, instead of one-layer interaction between agent and environment, we proposed hierarchical multi-layer intelligent BDI approach in this study.

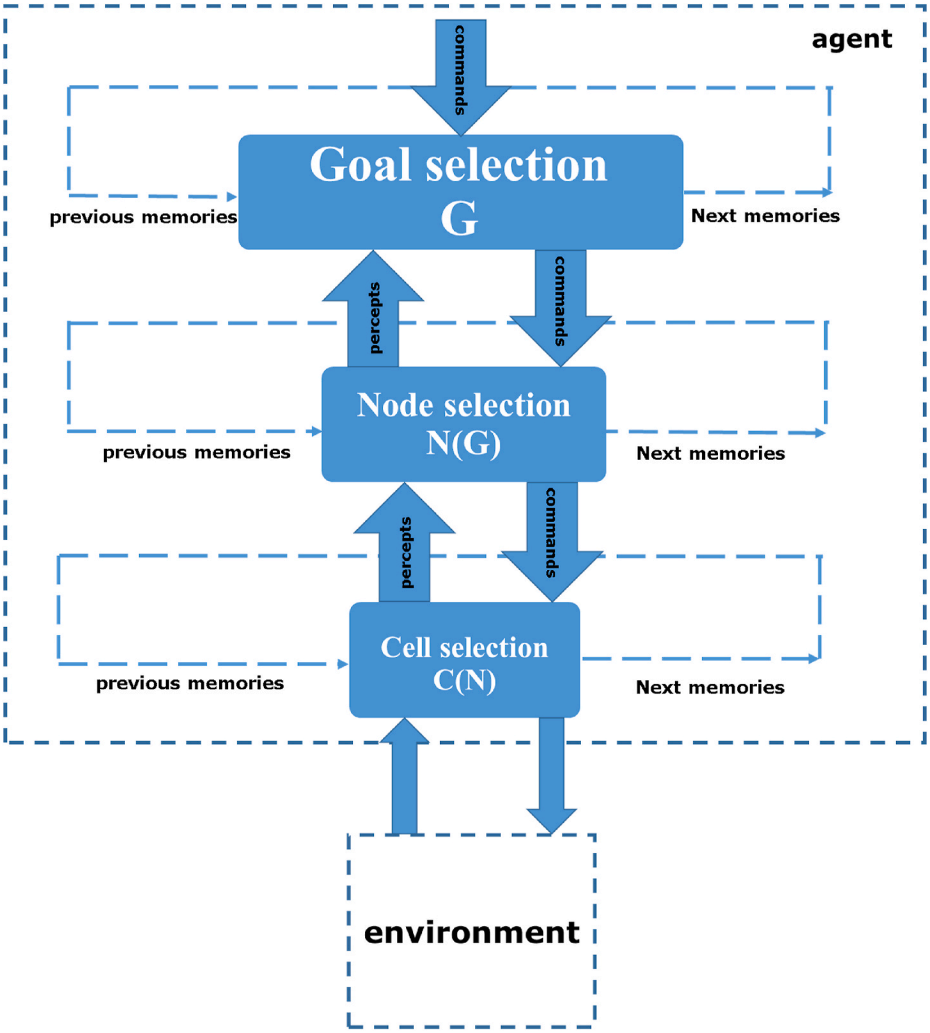


Fig. 2. The three-layer hierarchical agent system architecture of the agents' decision-making process.

– Environment simulation

The environment can be the internal spaces of a building, shopping centre or a transportation station where different people scattered all around. There are some ABM studies simulated the environment in a cellular framework in which the size of each cell is often equal to the space occupied by an agent at the specific time (Song et al., 2019). In these models, the agents will choose the next step (next cell) according to some predefined rules (CA approach). However, in the real world, the decision-making process of agents at each time step is a very complicated issue depending on the physical and psychological characteristics of people and also the environment.

In the current study, a three-layer hierarchical decision-making architecture is assumed (Fig. 2). In hierarchical agent system architecture, each layer sees its below layers as a virtual body from which it gets perceptions and to which it sends commands (Poole and Mackworth 2017). For example, in a post-earthquake situation, people first define their main goal, which can be immediately going out, helping others, finding particular items, or searching for their friends. They will then decide their next area to go to achieve their goal (going out of a room, go to the kitchen to find something, use stairs, etc.) and finally at the lowest level they will choose their steps to reach the selected area.

The outlook of the agent (which can be called the planning horizon), at lower levels, is shorter than that of the higher ones with respect to the time dimension. The lower-level layers often refer to the quick reactions of the agent to the surrounding world; therefore, they run faster. Inside each layer depicted in Fig. 2, there is a BDI framework for the decision-making process to select appropriate goals, nodes, or cells. The point is that a whole lower layer is the action block for the upper layer in the BDI structure. So the node selection layer is the action block for the goal selection, and similarly, the cell selection layer is the action block for the node selection.

The main challenge is the overall movement direction at each time step rather than choosing the next cell. Accordingly, this study uses a mixed graph and a cellular mode in order to model the different layers of the environment which agents deal with at each time

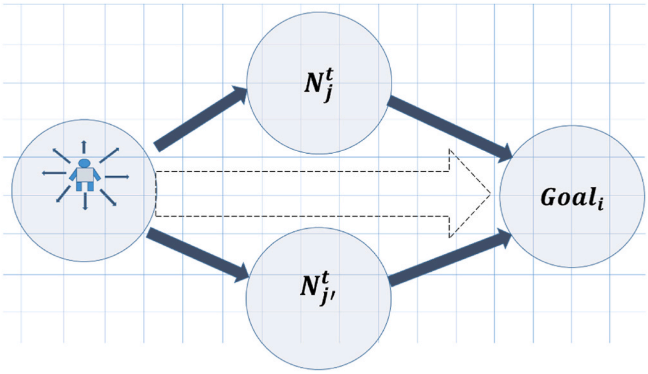


Fig. 3. The cellular movement of an agent within the hierarchical structure.

step. In the hierarchical approach, the agents make decisions in top-down structure (as shown in Fig. 2). At the top level, they will choose their primary goal, which can be finding the closest exit door, helping others or finding some particular objects. After the primary goal, they will explore the environment to reach that goal which means that they will choose the main direction of movement. Selecting the main direction does not mean selecting the next step; it means that they will intelligently decide their next region of the environment. For example, if they are in a room and intend to evacuate from the building, they will decide to go out of the room first so the next main direction will be the room's exit door and at the next step, they may choose a corridor and so on. After selecting the main direction at the lowest level of the decision process, they will choose their next step according to their own preferences and environmental variables. To say it in short, the agents will choose the next cell to reach the next chosen area, and they choose the next area to reach their main goal.

So the environment is a network consisting of the nodes and links in addition to the cellular platform. While each cell represents small space ready to be occupied by agents, each node represents a specific region that agents can visit through their travel and each link just show whether there is any direct relation between tow nodes or not. More formally, if there is a link between a pair of nodes, it means that the agent can go directly from one to the other (Fig. 3). The size of the cells is set according to the occupied space by the body ellipse of agents. In order to simplify the calculations and according to the literature, each cell is assumed a 50 cm * 50 cm square (Pheasant and Haslegrave 2005).

– Agents' simulation

After describing the details of the environment, in this subsection, we explain the physical aspects of simulated agents of the model in details. Nelson and Mowrer believe that in a crowd movement, the human instinctively avoids physical contact with others (Hurley et al., 2016). So, it can be said that each agent has a private zone which is based on the "body ellipse" (Fruin 1971; Crooks et al., 2015).

The next important variable for the physical attributes of agents in an evacuation simulation is the speed of the agents. In the current study, like the real world, each agent has his/her own particular speed. According to the physical condition of the body, the speed will differ from one agent to the other. So a random normal distribution value is used in order to assign different speeds to different agents. Naturally, these speeds will vary in various states of the agents (normal state, in a rush, frightened, stuck in queue, etc.). Generally, two status of speed were assumed for different agents in this study: normal speed and emergency speed. However, the average speed of men also differs from women (Huang and Ma 2010). The mean (μ) value of the normal distribution for men in normal status is 1.2 m/s, and in an emergency is 2 m/s. For women, these values are 1 and 1.8, respectively (Zębala, Ciępka et al., 2012). The standard deviation (σ) is assumed 0.15 and also the maximum, and minimum speed (high and low thresholds) is assumed 2.5 m/s and 0.3 m/s, respectively.

– Movement simulation

According to the classical belief-desire-intention (BDI) models, agents initially observe the surrounding environment and get the information (belief) to define a goal for themselves (desire); then to reach the goal they will plan their movements and do the action (intention). There are three questionable challenges in these models, which this paper aims to answer. The first one is agents always may not get enough correct information by observing or any other inputs from the environment because they may not be thoroughly familiar with the dynamic network as we mentioned before. The second one is that even if we assume that there is enough information for all the agents, there is no guarantee that all the agents choose or do the same action as the human beings have different tastes and preferences. Therefore, the agents might choose the wrong paths. The third challenge is that they should learn from their past exploration experiences through the network not to repeat their previous wrong choices. The first two issues address the inherent uncertainty exist in the decision-making process, and the third one is adding more intelligence to the agents.

The main algorithm of the proposed model contains two sub-algorithms. The main algorithm must continue until the agent reaches his/her goal. Fig. 5 depicts the flowchart of the agent movement algorithm. The dashed blocks show the BDI structure for the second

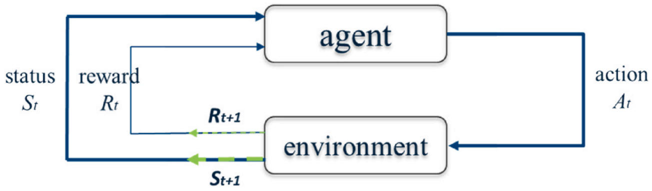


Fig. 4. The agent-environment interaction in a decision process (Sutton and Barto 2017).

layer (node selection). To summarise the whole process, we can say that at each time step, after choosing their main goal according to the overall inspection, agents update their information by observing the surrounding environment (S_t (O_i)). Then, they evaluate the previously used link according to the updated state and old memories (Q-value$_t$ = f (Q-value$_{t-1}$, S_t)). Then they should choose or review their main goal according to new information. Next, they choose the next link according to the main goal and the available links' Q-values. Finally, they do the action and go toward the next node (through the chosen link) by inspecting and choosing their next step to reach a specific area (A_t). The following section outlines the learning process and the details of the algorithms.

– Learning process

In this section, we elaborate the details of updating the Q-values of the links by using the reinforcement learning algorithm branch from the machine learning. As biological learning systems originally inspired the core algorithms of reinforcement learning, it is the closest to human behaviour among the other machine learning algorithms (Sutton and Barto 2017).

The basic concept of the model is based on the fact that all the agents are trying to maximise their reward signal by choosing the different links and reaching to different nodes. Fig. 4 shows the learning interaction between an agent and the environment. By choosing any action and going to a specific node, the agents change the status of the environment and simultaneously take a reward from the environment. The reward can be positive, which means the chosen action is getting them to their goal or negative, which means the chosen action is not appropriate enough to reach the final goal.

At each time step (t) the agent is in a specific status of the environment S_i (S_t ε S). After choosing an action (A_t) according to his perceptions and moving toward the chosen direction he will be received a reward by the environment R_{t+1} (R_{t+1} ε R) and at the same time, he will put himself in a new status S_{i+1}. Therefore, the sequence of the learning process is as follows:

S_0, A_0, R_1, S_1, A_1, R_2, S_2, A_2, R_3, …

To update the Q-values, an equation based on the Bellman equation is used as follows:

$$\begin{aligned} &Qmax_j = \max\left\{Q - values\ of\ the\ chosen\ node\ N_j\right\} \\ &Qvalue_i^t = (1-\alpha)Qvalue_i^{t-1} + \alpha\left(reward_j + \gamma Qmax_j\right) \end{aligned} \tag{1}$$

$Qvalue_i^t$ is the Q-value of the link i at the time t which shows the link evaluation by an agent who has just used the link. $reward_j$ is the reward of the chosen node (N_j) which is a constant value for the node according to their position and situation in the environment. The exit nodes clearly have positive rewards, while the dead-end nodes have negative ones. In this study, we have two types of nodes: exit nodes and normal nodes. All the normal nodes have an equal amount of negative reward, and all the exit nodes have the positive ones. This will lead to a convergence learning procedure. α and γ are the learning rate and discount factor, respectively, both taking an amount between 0 and 1. α learning rate represents the weight of new information (new learning) against the previous information. It can be clearly found out from the equation that if we have $\alpha = 0$ the q-values will not be updated, and they will remain constant. Now if we assume $\alpha = 1$ ignoring its previous value, the new q-value will be updated just based on the reward of the chosen node and its situation. γ, the discount factor, will add the weight of the future options to the q-value of the link.

Algorithm 1. Stop criteria: if the agent has reached to his goal (it can be the exit node) the algorithm should stop.
Repeat.

Step1. updating the information by observing the surrounding environment: S_t:= (N_t)

Step2. analysing the information and inputs in the new status to evaluate the used links (Q-values$_t$) and configuring the next (Q-values$_{t-1}$): learning process

Step3. updating the main goal according to the updated information: Gt (St)

Step4. selecting the next link (the next node or area to go) according to the main goal and the available Q-values: Algorithm 2

Step5. take action (A_t): Algorithm 3

Step 6. if it is the next node then t: = t+1 and Return to the Step1
Until the agent is on the goal node.

Algorithm 2. Reviewing the literature, we can find out that the classical decision theory is a set of mathematical techniques for making decisions about what action to take when the outcomes of the various actions are not known (Deljoo et al., 2017). To apply this

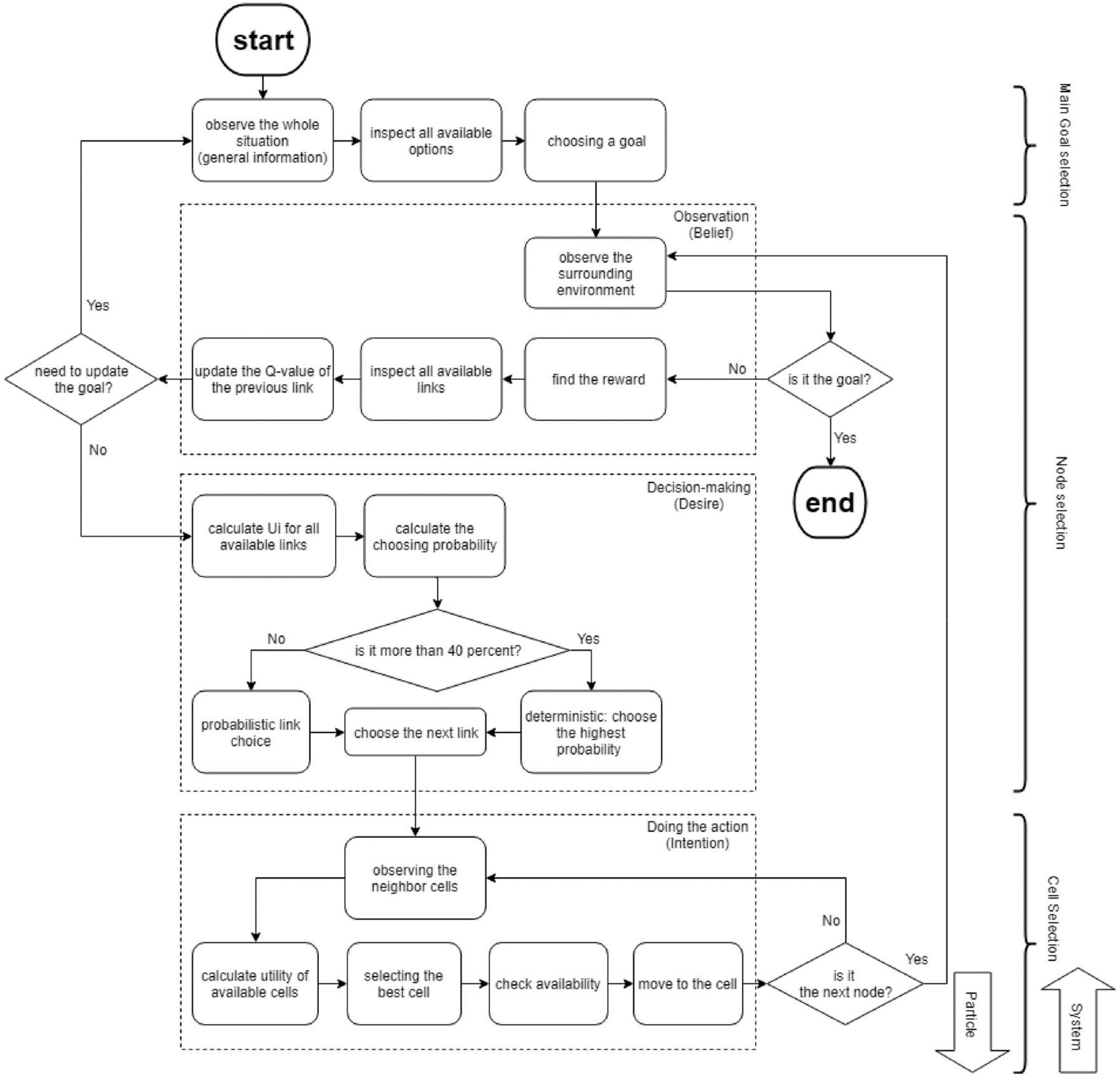


Fig. 5. The flowchart of the proposed hierarchical model for the agents' movement during the evacuation process.

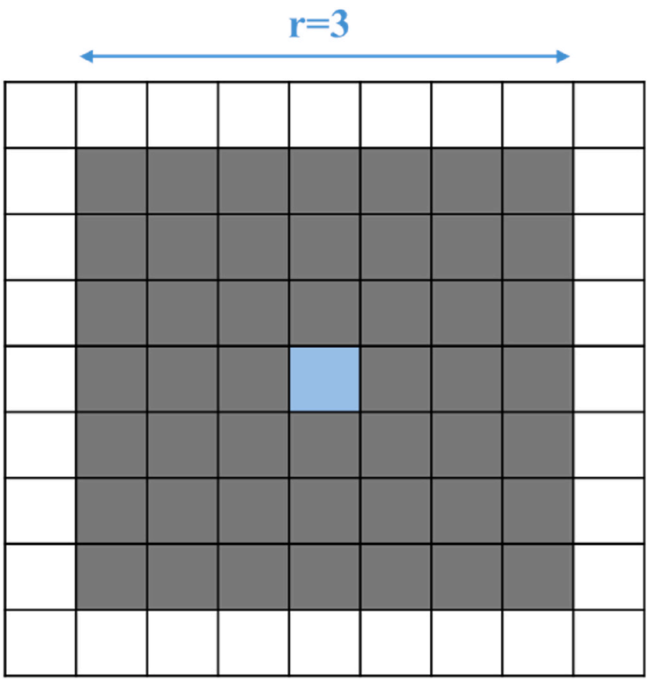


Fig. 6. The extended Moore neighbourhood (r = 3).

theory into the agent-based model, we should consider that the uncertainty exists in all levels of the decision-making process in a complex dynamic network of environment. Therefore, a Logit-based approach was used where at each specific status of the environment (say S_t) the agent evaluates the available next options in his mind according to the amount of utility they get from different alternatives. The mixed logit approach can be used in order to consider different tastes of agents, however in this paper to simplify the whole calculations we used a simple multinomial logit approach with two variables in the utility function. We simulate this automatic brain process through a normalised scoring procedure where the scores (utilities) are a function of Q-values and other variables (such as the amount of hazard or congestion) of the available links. So at each state of the environment, the probability of the choosing an option (a link) will be calculated (P (A_i)) and the agents will choose the options stochastically according to the utility of each link. If A_i is the subset of the A (the set of the available actions) at the time t, so:

$$P: A_i \varepsilon [0,1]$$

$$P(A^t_1) + P(A^t_2) + P(A^t_3) + \ldots + P(A^t_i) = 1 \tag{2}$$

The inputs for this algorithm are the main goal, the set of available links, the Q-values of the available links which have been updated through the learning process before. The output of the algorithm is defining the next node by the probabilistic decision-making process. Pay attention that choosing the next link will be literary choosing the next node as well as each link leads to a node.

In order to have a more realistic model which has better convergence, we assume that if the probability of choosing an option is more than 40 percent the selection process will become deterministic. It means that for the options whose amount of probability is more than 40 the agents will certainly choose the best one (with the highest probability) (Office of the Prime Minister's Chief Science Advisor, 2016).

Step1. assigning the utility function to each of the available links:

$$U^t_{ni} = \propto_n Q^t_{ni} + \beta_n H^t_{ni} \tag{3}$$

where:

U^t_{ni}: The utility of the alternative i at the time t for the agent n
Q^t_{ni}: Q-value of the alternative i at the time t for the agent n
H^t_{ni}: The amount of hazard exists at the alternative i at the time t for the agent n
$\propto_n$ and β_n: The weights of Q-value and amount of hazard for the agent n respectively (perceptual weights are assumed in this study)

The considerable point is that since only differences in utility matter, it is necessary to normalise the amounts of weight parameters ($\propto and\ \beta$) in the utility function. So we will have:

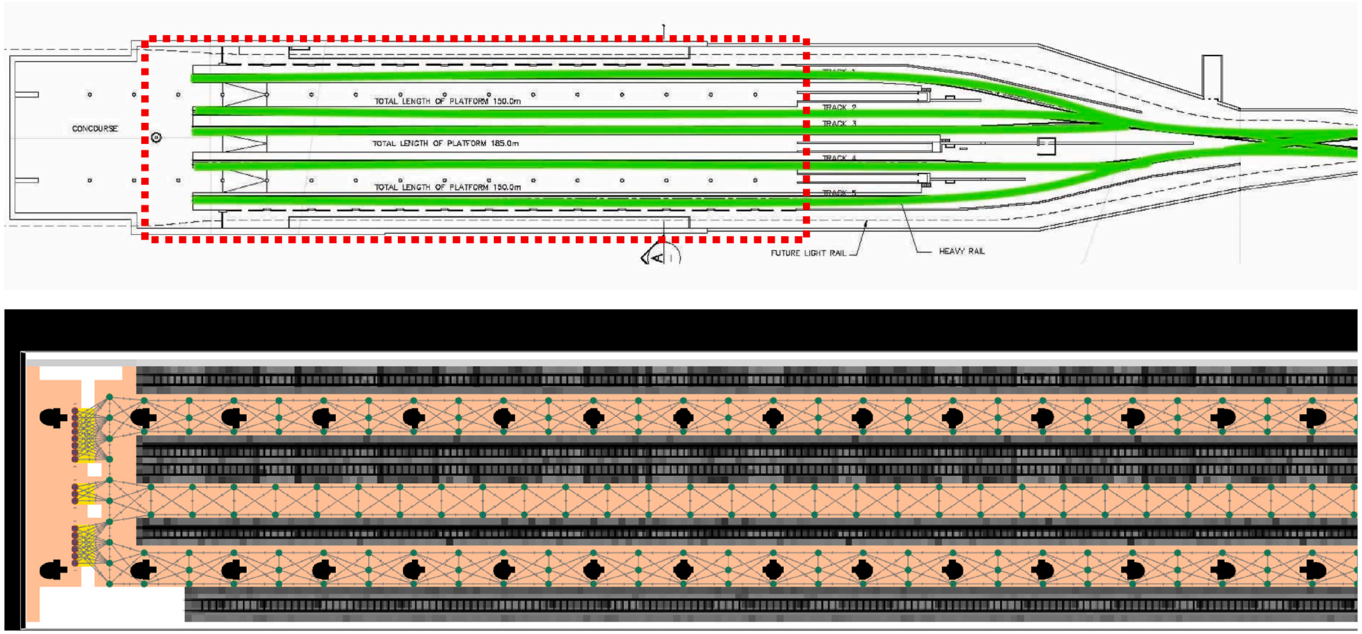


Fig. 7. (a) The real map of the platform of the B2 in Britomart station, dashed box shows the desired area for simulation (b) a view of the simulated platform of the Britomart station.

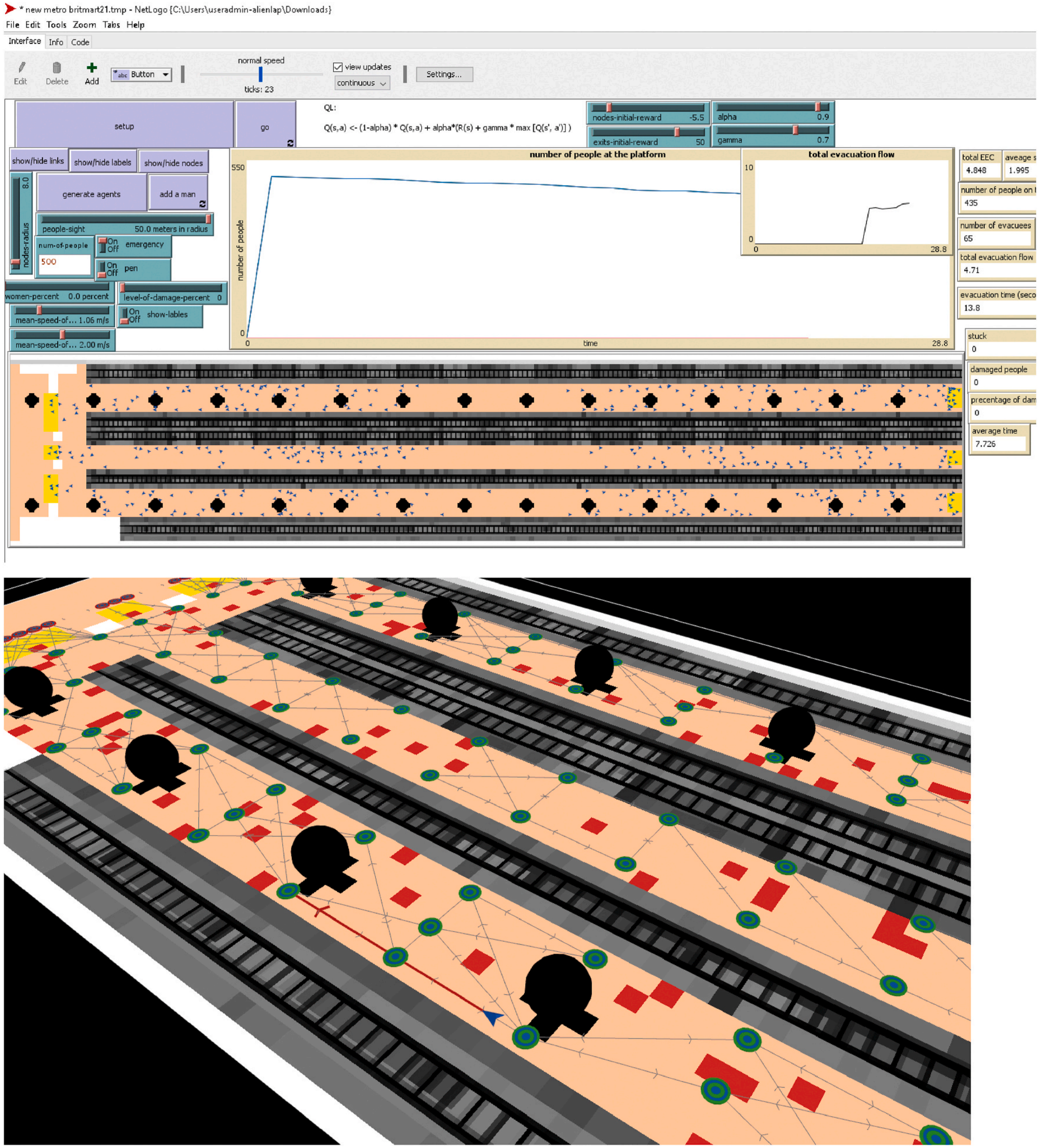


Fig. 8. (a) Operational interface of the whole model in NetLogo, (b) Screenshot of a single agent during movement toward a selected area among the dynamically damaged network in environment.

$$\alpha+\beta=1$$

It is implied that it is assumed people will choose the alternatives according to their distance from the goal and the amount of hazard existed in each link.

Step2. calculating the choosing probabilities of the links according to the amount of utility:

$$P^t_{ni} = \frac{\exp\left(\propto_n Q^t_{ni} + \beta_n H^t_{ni}\right)}{\sum_{j-1}^{j}\exp\left(\propto_n Q^t_{nj} + \beta_n H^t_{nj}\right)} \tag{4}$$

where P^t_{ni} is the logit probability of alternative i evaluated at the time t for the agent n with J the total number of alternatives.

Step3. defining the next node: if the maximum amount of the probability is more than 40 then introduce the node as the next node, otherwise choose the next node in a stochastic manner.

Algorithm 3. This algorithm is quite similar to the algorithm1, but the difference is that the choice process will be among the available neighbour cells instead of the available links. The extended Moore neighbourhood approach was used in this paper. Fig. 6 shows the extended Moore neighbourhood for r = 3. The amount of r of the extended neighbourhood depends on the speed of the agents. So, each agent has his/her own specific neighbourhood cells according to his/her physical ability.

To implement the speed in the coding of the simulation, we used the definition of the speed, which means passing the length in a specific time. So, when the agents are walking with the speed of 1.5 m/s he/she will pass three cells in each second (r = 3)- (3(number of cells) * 0.5 (length of each cell) = 1.5 (total passed length)). So the amount of r for each agent is the smallest integer greater than or equal (rounding up) to the result of speed divided by 0.5.

$$r := ROUNDUP\left[\frac{speed}{0.5}\right] \tag{5}$$

This time the agents already know the main direction of their movement (they have already chosen the next node), but they will choose their next step toward the chosen direction. The point is that this procedure will be deterministic, unlike the link selection process. It means that the cell selection will be according to some reasonable constant defined rules.

Stop criteria: if the agent has reached to his chosen node (already definite from the algorithm2), the algorithm should stop.

3.1. Repeat

Step1. updating the information by observing the surrounding environment (neighbour cells)

Step2. selecting the best cell according to some predefined rules which directly depend on the main direction (chosen node) and availability of the cell

Step3. move to the next cell according to the physical attributes of the agent such as speeds

Step4. updating the dynamic status of the cells such as the occupied status of the cells or the amount of the danger

Step5. if it is not the next node yet then t: = t+1 and Return to the Step1 otherwise stop and continue algorithm1

Until the agent is on the next chosen node.

4. The case study: Britomart subway platform

As an illustration for the conceptual model of the study, the walking platform of the Britomart metro station platform is selected as the case study (Fig. 7). Britomart Transport Centre is the major transportation hub of Auckland Transport (AT) in New Zealand. Although there will not be any complicate exploration process by the agents on the platform to find the exit areas, the Britomart platform was chosen due to its appropriate and simple physical situation to illustrate the conceptual model. Also, a destructive event is assumed to be happening during the evacuation process, which mimics a dynamic network of the environment. Fig. 8 shows the interface of the NetLogo and a screenshot which depicts the movement of an agent through the damaged environment.

Since the approach is a kind of prototyping model, no calibration has been conducted for utility function which can be done in future works. But a scenario-based approach is used to illustrate the consideration of different preferences. For $\propto_n$ and β_n in equation (3), it is assumed that there are three types of agents which randomly distributed on the platform:

Type 1 who prefers to go through the nearest path: *α=0.7, β=0.3*.

Type 2 who prefers to go through the safest path: *α=0.3, β=0.7*.

Type 3 who give the same weight to the distance and the amount of hazard: *α=0.5, β=0.5*.

It is assumed that due to a destructive event (it can be earthquake) some elements or areas of the platform will be randomly and dynamically damaged during evacuation so people may be injured or they may be forced to change their movement direction at each time step. However, the injuries and fatalities are not focused in this paper, but it can be considered in future studies. The severity of this destructive event can be adjusted by the developer through different scenarios.

Table 1
The tests used for the verification of the simulation model.

No.	Test name (type)	objective	Reference	Expected result
1	Speed in a corridor (quantitative)	maintaining an assigned walking speed over time.	IMO Test 1	The occupant should cover the distance of the corridor in 40 s
2	Movement around a corner (qualitative)	correctly simulate the boundaries of a scenario.	IMO Test 6	successfully navigate around the corner and among the columns without penetrating the boundaries
3	Horizontal counter-flows (qualitative)	the ability of models to simulate counter-flow.	IMO Test 8	The recorded time increases as the number of persons in counter-flow increases
4	Dynamic availability of exits (quantitative)	the capabilities of the model to represent the dynamic availability of exits.		The expected result is that Exit 1 is not used by the occupant.

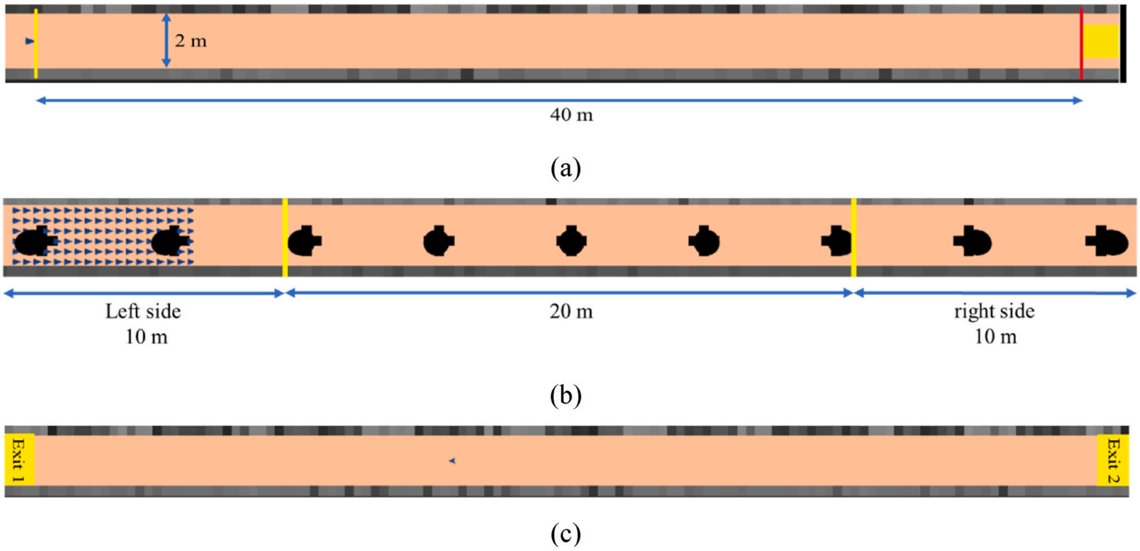


Fig. 9. Geometries of the tests (a) test 1-speed in a corridor (b) test 3-horizontal counter-flows (c) test 4-dynamic availability of exits.

– ***Validation and verification***

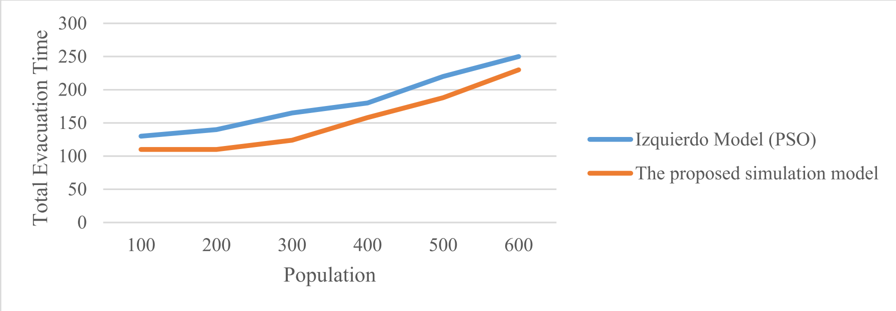
For verification and validation of the model, the basic requirements derived from the literature have been tested (Lubaś et al., 2014). The basic tests, including reasonable movement and navigation, pedestrians' ability to maintain assigned walking speed or avoiding boundaries (walls), and choosing the best direction toward the exit doors, have been successfully passed through 4 different scenarios. An assumption is that the pre-evacuation times for all agents set equal to 0 as the focus of the simulation is on the direction choice and movement during evacuation. Therefore, all the agents will start to evacuate as soon as the simulation runs. Table 1 shows the details of applied tests to verify the simulation based on a modified MSC/Circ.1238 provided by the International Maritime Organization (IMO) applicable for building evacuations (Ronchi et al., 2013; International Maritime Organization 2007).

Test 1: In this scenario, an occupant with a walking speed of 1 m/s is walking along the corridor 2 m wide and 40 m long figure (from the yellow line to the red line in Fig. 9-(a)). This test seeks the maintenance of assigned walking speed during the simulation. In the study, the test is organised exactly the same as the regulations. The average time for 30 runs was 39.863, with a variance of 0.625.

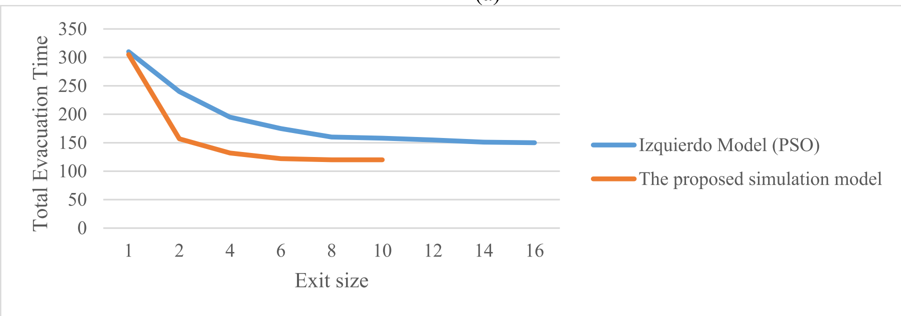
Test 2: This test tries to verify the ability of the model to simulate the movement through corners and obstacles. Twenty agents are uniformly distributed randomly in the walkway areas with a walking speed of 1 m/s. The quality of navigation through corners and among columns have been tested. The results of multiple runs showed that all the agents were able to distinguish obstacles and also choose the nearest exit.

Test 3: Step 1: One hundred persons move from the left side of the platform to the right side of the platform (separated by the yellow line in Fig. 9-(b)), where the initial distribution is such that the left side is filled with maximum possible density. The time the last person passes the yellow line on the right side is recorded. Step 2: Step one is repeated with an additional ten, fifty, and one hundred persons on the right side. These persons should have identical characteristics to those on the left side. Both sub-populations move simultaneously in the opposite direction, and the time for the last persons from the left side to the right side is recorded. The recorded time correctly increased as the number of persons in counter-flow increased.

Test 4: Insert an agent at the left half of the platform near to the middle point (in a way that exit 1 is closer to the agent) with a constant walking speed equal to 1 m/s, as shown in Fig. 9-(c). Exit 1 becomes unavailable after 1 s of simulation time. The agent should be able to change its decision and direction and use exit 2. The hierarchical approach of the model enabled the simulated agents to



(a)



(b)

Fig. 10. Model to model comparison of the study results for total evacuation time according to (a) population and (b) exit size to the results of Particle Swarm Optimization.

change their goal perfectly in this test. In all 30 runs (out of 30 runs-100 percent) of the runs, the agent chose the exit 2 less than 2 s of simulation time.

– **Model to model comparison**

Another recommended way to verify if the agent-based simulation model is working properly or not is model to model comparison (Xiaorong et al., 2005). One of the studies which focused on the pedestrian evacuation time using the Particle Swarm Optimization (PSO) by Izquierdo has been used as the benchmark to compare the evacuation results (Izquierdo et al., 2009).

Twenty replications were performed for each test scenario to improve reliability of results, and the mean value was considered for the total time based on the two variables population and size. Fig. 10 shows the changes in total evacuation time with the population and exit size. It should be noted that the exit width experimented in the study of Izquierdo et al. was 6 m while it was 3 m in this study. However, the distance of people from the exits is critical, which was relatively less in our study. Consequently, the simulation model proposed in this study has shown less time. Nevertheless, the slope of evacuation time increase with the population is almost the same in both studies (the slope $\approx$ 20).

The evacuation time for small population size (in Fig. 10-a) and large exit size (in Fig. 10-b) is not changing significantly (the line slope is near 0). This is because congestion does not yet play a role in evacuation time in these areas, and pedestrians with the slowest speed determine the total evacuation time. The general slope of the evacuation time change trend in Fig. 10 shows that the proposed model is correctly simulating the evacuation process.

– Simulation results

The population size and level of severity for the destructive event were the two independent variables of the simulation, which separately had four groups. The population values were 300, 600, 900, and 1200 (number of agents) and there were also four conditions for the level of severity including no damage (level 0), level 1, level 2, and level 3. Therefore, we had 16 scenarios which we ran the simulation 4 times for each.

Fig 11 shows the number of people on the platform at different software time-steps for different population groups and different severity levels of a destructive event. The dashed lines show the trend lines of each curve, which the slopes depict the flows of evacuation.

Table 2 shows the overall descriptive statistics (values of the mean and standard deviation) for four variables of total evacuation time, the average evacuation time for each agent, the average flow of evacuation, and the maximum evacuation flow as the dependent variables. As we have two fixed variables (independent variables) which have their own different groups (4 groups for each), we conducted two-way ANOVA analysis for each dependent variable separately (4 ANOVA analysis). The three null hypotheses for each

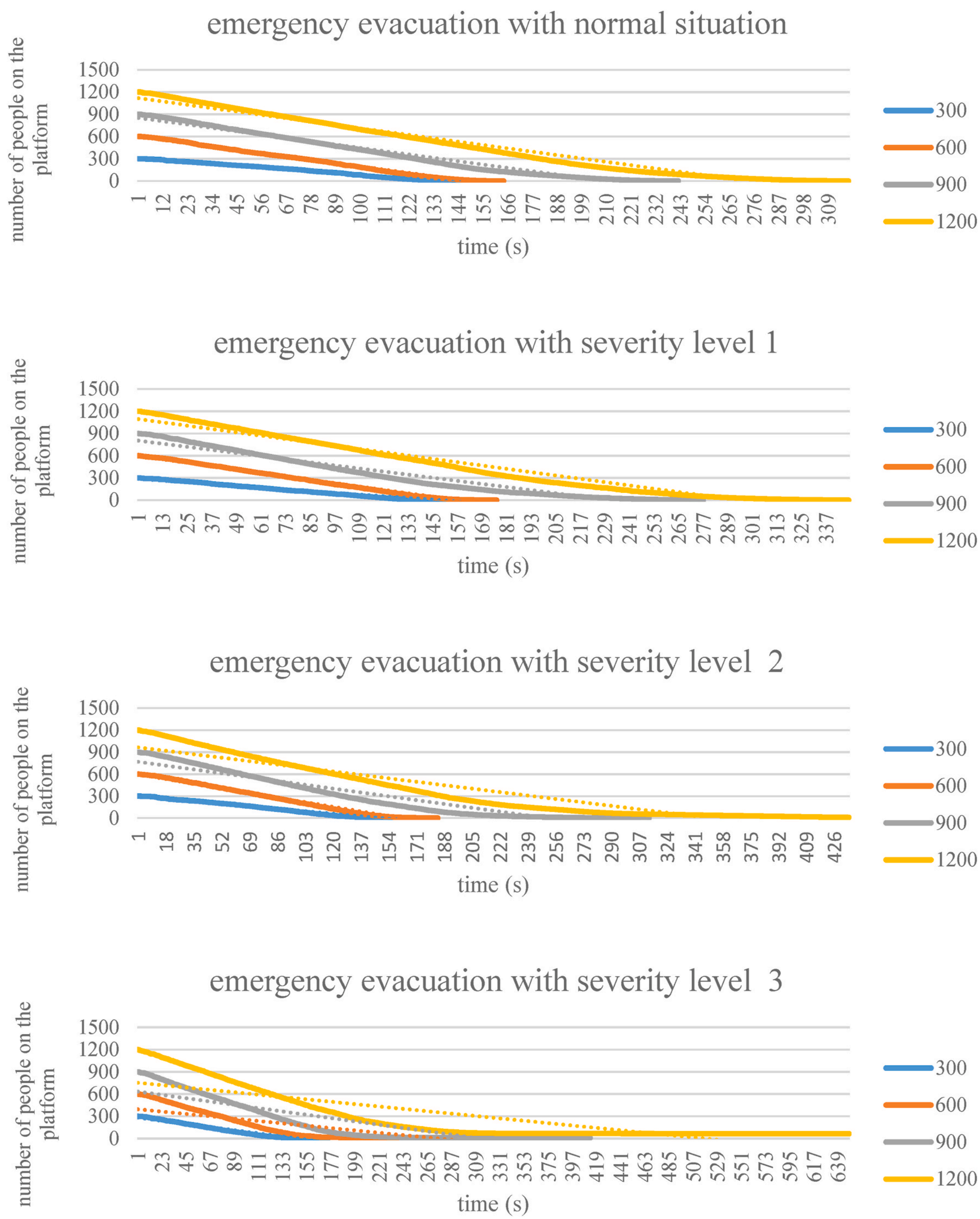


Fig. 11. People evacuation through different severity levels of damage.

dependent variable was as follows (It is written for MEF):

H0. population will not affect MEF

H0. different severity levels of the destructive event will not affect MEF

H0. population and severity level interaction will not affect MEF

Before starting the ANOVA, we did the homogeneity test which the Levene's test verified the equality of variances (homogeneity of

Table 2
Overall descriptive statistics of all 16 scenarios.

population	severity level of damage	Maximum Evacuation Flow (MEF)		Total Evacuation Time (TET)		Average Evacuation Time (AET)		Average Evacuation Flow (AEF)	
		Mean (person/second)	S. D.	Mean (second)	S. D.	Mean (second)	S. D.	Mean (person/second)	S. D.
300	no damage	4.96	0.50	90.00	2.35	41.14	0.64	2.97	0.09
	severity level 1	5.08	0.35	94.35	10.03	40.90	1.65	2.86	0.32
	severity level 2	4.96	0.42	101.55	8.36	41.47	1.43	2.65	0.23
	severity level 3	4.63	0.25	124.35	20.84	42.17	2.56	2.31	0.18
	Total	4.91	0.39	102.56	17.58	41.42	1.61	2.70	0.33
600	no damage	8.04	0.44	109.20	9.61	44.99	1.50	4.93	0.43
	severity level 1	7.83	0.53	111.75	4.58	45.46	1.24	4.77	0.19
	severity level 2	7.54	0.37	119.40	13.95	46.17	0.86	4.52	0.54
	severity level 3	7.29	0.21	245.40	97.22	47.48	1.28	2.54	1.29
	Total	7.68	0.47	146.44	73.82	46.03	1.47	4.19	1.20
900	no damage	8.67	0.30	148.35	6.32	58.78	1.34	5.43	0.24
	severity level 1	8.71	0.28	149.55	11.24	58.98	0.72	5.40	0.38
	severity level 2	8.92	0.22	154.20	23.04	58.50	1.16	5.30	0.70
	severity level 3	8.75	0.22	283.50	180.22	59.59	2.41	3.56	1.60
	Total	8.76	0.25	183.90	100.83	58.96	1.44	4.92	1.15
1200	no damage	9.00	0.41	198.15	16.37	74.58	2.35	5.44	0.45
	severity level 1	9.04	0.32	201.30	19.01	76.09	1.91	5.36	0.50
	severity level 2	9.00	0.30	260.70	107.45	76.97	1.28	4.52	1.33
	severity level 3	9.46	0.90	443.40	160.30	78.01	3.31	2.83	1.61
	Total	9.13	0.52	275.89	134.96	76.41	2.46	4.54	1.46
Average	no damage	7.67	1.70	136.43	43.67	54.87	13.64	4.70	1.09
	severity level 1	7.67	1.64	139.24	43.77	55.36	14.20	4.60	1.12
	severity level 2	7.60	1.71	158.96	80.81	55.78	14.22	4.25	1.24
	severity level 3	7.53	1.96	274.16	165.77	56.81	14.40	2.81	1.27
	Total	7.62	1.72	177.20	110.76	55.71	13.79	4.09	1.38

Table 3
ANOVA Test of Between-Subjects Effects for all the dependent variables.

		MEF		TET		AET		AEF	
	df	F	Sig.	F	Sig.	F	Sig.	F	Sig.
pop	3	347.751*	.000	17.085*	.000	1280.100*	.000	23.213*	.000
Level of damage severity	3	.396	.756	13.456*	.000	3.545	.021	18.715*	.000
pop * severity level	9	1.526	.166	1.363	.231	.468	.889	1.176	.332

variances) for EEC and average evacuation time for one agent (p-value = 0.331 and 0.176 respectively). But for two other variables-average flow and total evacuation time-the p-values were slightly smaller which showed we could not totally reject that the error variance of the dependent variable is equal across the groups. But the point is that when we conducted the normality test, we understood that exactly for these two variables, we have a problem with the normality test. However, the non-parametric Levene's test based on median verified the homogeneity of variances. The reason is that when we have some agents get stuck in some scenarios due to the destructive event, the total time and the average flow will have abnormal extremum in their curves so they won't be normally distributed anymore. These non-normal curves represent that one or a group of people had some problem during the evacuation, and they spend more time exploring and finding the path to exit. However, for large numbers of runs this problem won't exist so we can neglect this homogeneity test for them and ANOVA is still usefully applicable for them. The whole data analysis was done in the IBM SPSS statistics-version 25 software.

4.1. Maximum evacuation flow (MEF)

It can be a question of why the maximum evacuation flow is important in an evacuation process. Often the maximum flow (let's say through an exit door) is used to determine the capacity (of the exit door). In this study, the maximum flow of people evacuating from the Britomart station platform was investigated in order to find the empirical capacity of the exit areas of the platform. The flows were calculated in a period of 10 s. Although the flows are captured for 10 s, the unit of MEF is person per second. Therefore, the total number of peoples evacuated in 10 s will be divided by 10 in order to calculate MEF. The same calculation will be applied to the average evacuation flow. Table 3 shows the between-subject effects which are clearly showing that the MEF is highly affected by the population ($F = 347.751$ and $p < 0.05$), But not by the severity level ($F = 0.396$ and $p = 0.756$). Also, we don't have significant interaction effect, ($F = 1.526$ and $p = 0.166$). That is exactly what we expect from the maximum flow as it is supposed to show the capacity according to the physical attributes of the platform or its exits areas. So MEF commonly should not be directly affected by the

Table 4
Multiple Comparisons between internal groups of the population regarding MEF.

	Population (I)	Population (J)	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Tukey HSD	300	600	−2.770833[a]	.1447754	.000	−3.156135	−2.385532
		900	−3.854167[a]	.1447754	.000	−4.239468	−3.468865
		1200	−4.218750[a]	.1447754	.000	−4.604051	−3.833449
	600	300	2.770833[a]	.1447754	.000	2.385532	3.156135
		900	−1.083333[a]	.1447754	.000	−1.468635	-.698032
		1200	−1.447917[a]	.1447754	.000	−1.833218	−1.062615
	900	300	3.854167[a]	.1447754	.000	3.468865	4.239468
		600	1.083333[a]	.1447754	.000	.698032	1.468635
		1200	-.364583	.1447754	.070	-.749885	.020718
	1200	300	4.218750[a]	.1447754	.000	3.833449	4.604051
		600	1.447917[a]	.1447754	.000	1.062615	1.833218
		900	.364583	.1447754	.070	-.020718	.749885

[a] The mean difference is significant at the .05 level.

Table 5
Multiple Comparisons between internal groups of the population regarding total evacuation time.

	Population (I)	Population (J)	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Tukey HSD	300	600	−43.875000	25.2204948	.315	−110.996127	23.246127
		900	−81.337500[a]	25.2204948	.012	−148.458627	−14.216373
		1200	−173.325000[a]	25.2204948	.000	−240.446127	−106.203873
	600	300	43.875000	25.2204948	.315	−23.246127	110.996127
		900	−37.462500	25.2204948	.454	−104.583627	29.658627
		1200	−129.450000[a]	25.2204948	.000	−196.571127	−62.328873
	900	300	81.337500[a]	25.2204948	.012	14.216373	148.458627
		600	37.462500	25.2204948	.454	−29.658627	104.583627
		1200	−91.987500[a]	25.2204948	.004	−159.108627	−24.866373
	1200	300	173.325000[a]	25.2204948	.000	106.203873	240.446127
		600	129.450000[a]	25.2204948	.000	62.328873	196.571127
		900	91.987500[a]	25.2204948	.004	24.866373	159.108627

[a] The mean difference is significant at the .05 level.

destructive event. However, the population evacuating from the environment can determine the maximum flows of the exit doors.

The between-group comparisons for the population properly confirm this idea where MEF values are significantly different between any two population groups except between 900 and 1200, where it reaches the platform's capacity (Table 4). It means that the population more than 900 will approximately use the full capacity of the exit areas for evacuation. At that point, in order to have more MEF, we need to improve the infrastructure or the width of the exit areas.

It should be noted that the MEF is investigated for the exit areas of the platform. Some studies use Emergency Evacuation Capacity (EEC) (Cheng and Yang 2012), which is calculated by the physical attributes of the exit doors and the speed of pedestrians:

$$C_{ex} = vk(l_{ex})$$

where.

C_{ex} is the capacity of the exit door (p/s),
Vis the evacuation speed at the exit door (m/s),
K is the density of people at the exit door (p/m^2), and
l_{ex} is the length of the exit door (m)

The definition of the EEC is the maximum flow of people evacuating from the corridor or exit door. Therefore, in this study, we can claim that we have empirically found the platform's total evacuation capacity by monitoring the evacuation flows during the evacuation process. This value is about 9 (person per second) for Britomart platform. We derived this amount from Table 2, where the mean total MEF value at 1200 population column is 9.13. Although capacity is a variable that should be calculated by the physical variables of the environment, this MEF can give us a proper perspective.

4.2. *Total evacuation time (TET)*

The definition of the total evacuation time is the overall time needed for all the agents to evacuate from the environment. According

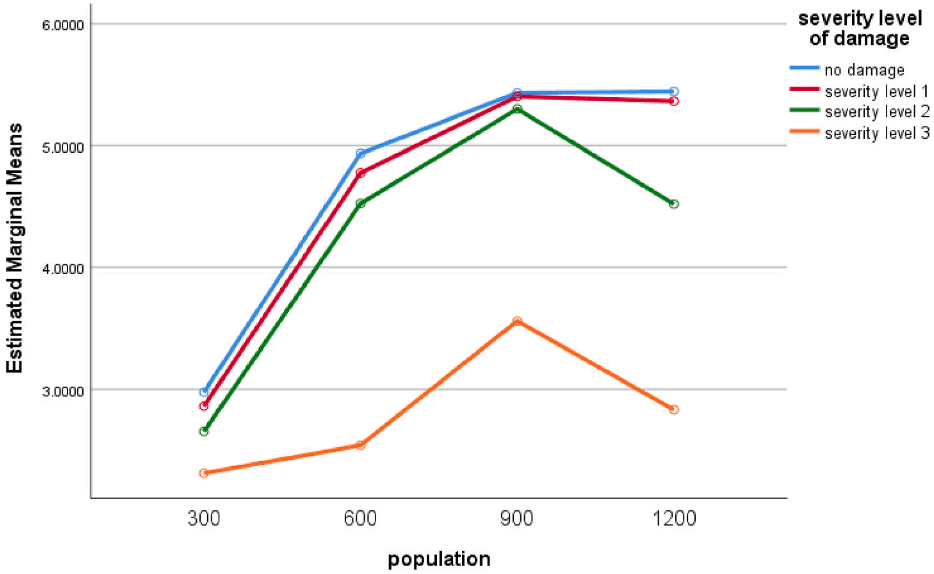


Fig. 12. Estimated marginal means of average evacuation flow.

to the two-way ANOVA, the total evacuation time is significantly affected by both population and level of destructive event ($p < 0.05$ for both) but not the interaction of population and severity level ($p = 0.231$). The inter-group analysis was done both for population groups and severity levels. The mean differences of the total evacuation time for 300–900, 300–1200, 600–1200, and 900–1200 were significant while in other multiple comparisons, we don't see considerable differences. The main reason for this issue is the congestion effect.

As can be seen from Table 5, there is a significant difference in mean total evacuation time between 1200 and other population groups. It represents the effect of congestion in this amount of population. We cannot see a significant difference between 300 and 600, because there is no congestion in these cases ($p = 0.315$). It means that the speed and the position of the agents at the platform will mainly determine the total evacuation time, not the population. So, the total evacuation time is determined by the slowest agent, who is located at the furthest position from the exit area.

4.3. Average evacuation time (AET)

The average evacuation time is the sum of evacuation time for all the population divided by the number of people. The between-subjects effects tests (Table 3) show that both population and severity level affect the average evacuation time. However, the F-value for the population is much higher than the severity level (1280.1, 3.545, respectively). Again the interactions are not significantly effective ($p = 0.889 > 0.05$). As the average evacuation time is determined by all individual agents in the simulation, it is different from the total evacuation time which is determined by the last agents who succeed to evacuate.

4.4. Average evacuation flow (AEF)

The average evacuation flow is the number of people who successfully evacuated from the platform per second in each scenario. However, similar to MEF, the evacuation flow is calculated by the number of evacuees during 10 s divided by 10. The between-subjects effects tests show the significant mean difference between both population and severity groups ($p < 0.05$ for both) but not the interaction effects ($p = 0.332$) (Table 3). However, the flow changes are a better index to analyse the quality of evacuation than the average flow. Fig 12 shows the marginal means of the average flow for different population groups and severity levels. As can be seen, the average flows for the 900 and 1200 population are approximately the same when there is no destructive event (the horizontal part of the blue curve). Again, it can be interpreted that these population groups are using the full capacity of the platform's exit areas. AEF dramatically decreases in 1200 population when the level of damage severity is 3.

Fig. 13 shows the different population flows through different time-steps in a normal situation (no-damage) versus severity level 3. The jumps on the last parts of the diagram in high severity case represent the large exploration time for the people who have changed their path because of the destruction.

5. Conclusion

In this paper, a novel hierarchical agent-based evacuation model was introduced, where the evacuees reasonably choose their next step and move through a dynamic network of environment when a destructive event takes place. Thus we have an autonomous

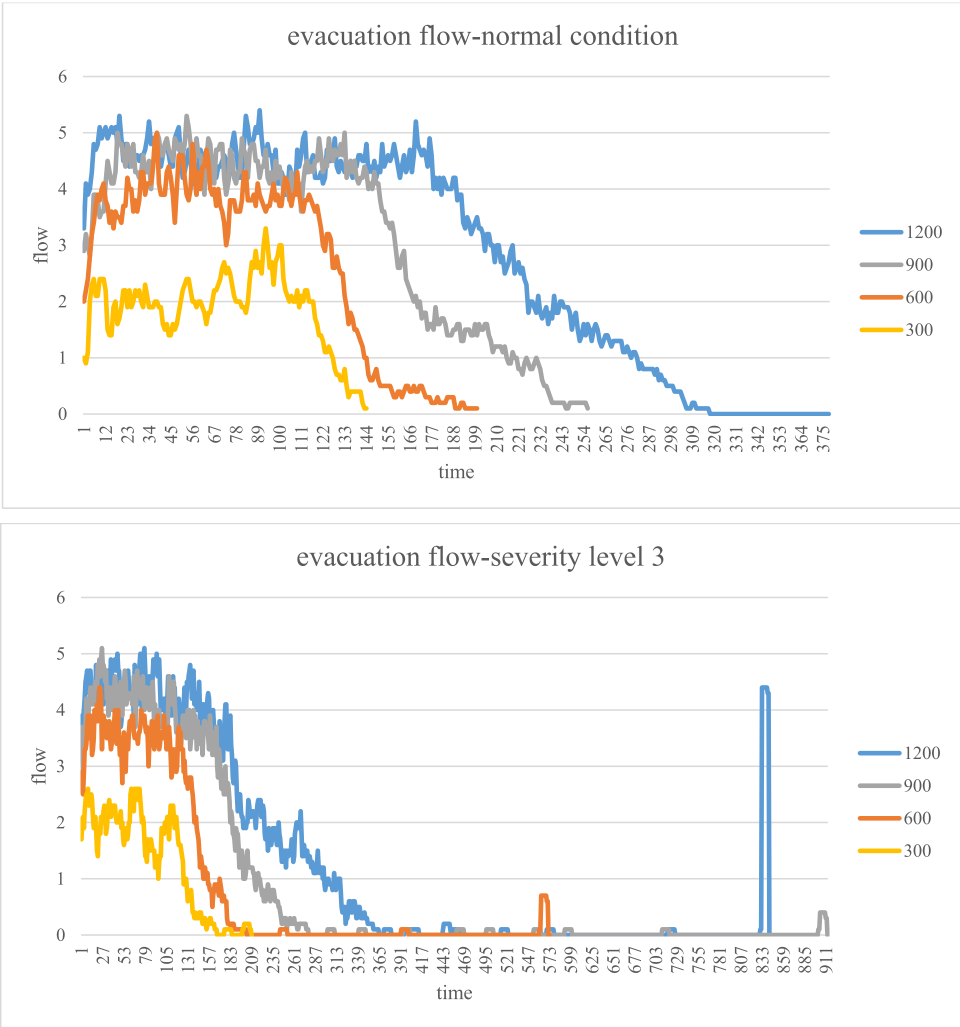


Fig. 13. Average evacuation flow of different population groups at (a) normal situation-severity level 0, (b) damage severity level 3.

population who can also be heterogeneous. Every individual has his/her own memory, experience, and knowledge toward the environment as well as his/her own physical and mental characteristics. Therefore, agents will choose their next goal, area, and cell according to their own attributes. The case study of Britomart transportation station (platform) was chosen to perform the model. The following conclusions are obtained:

- The model employs both graph-mode and cellular approach to simulate the hierarchy that existed in the human decision-making process during movement through an emergency where they are dealing with a dynamic network of environment.
- The whole hierarchical agent-based evacuation model was coded in NetLogo software and the model was successfully performed through 16 scenarios with 4 different population and level of severity of destructive event groups.
- The approach was successfully tested to simulate the evacuation process in the Britomart platform during an abstract destructive event. Four tests have been conducted to verify whether the simulation is working properly or not according to the modified MSC/Circ.1238 provided by International Maritime Organization (IMO) 2007.
- It is shown that the results can give an empirical overlook of the evacuation capacity of an environment by monitoring the maximum evacuation flow. The results showed that the total evacuation capacity of exit areas in Britomart platform is 9 (person per second).
- The test results showed that the total amount of MEF is not affected by the level of the destructive event at the platform, but the evacuation time is affected by the non-structural damages. Also, the congestion effects were analysed within different scenarios.
- The methodology proposed herein is able to simulate the details of intelligent exploration phenomenon during an evacuation, which includes people preferences and different tastes to choose their next step. Moreover, it can be used by designers and

managers to evaluate the building affordance in an emergency evacuation situation by showing the time needed for people to find the correct path after non-structural damages caused by destructive events.

It should be noted that although this study put a reasonable effort into introducing a comprehensive framework to consider different dimensions of evacuation behaviour, it is still a long way from reaching all details of psychological aspects of human. In future research, the mixed logit approach can be used to consider different agents' tastes. We will also focus on two potentially vital points to enhance the model: the first one is coupling the proposed approach with some other constructional management tools such as BIM or SRM to invent a unified standard tool for evacuation evaluation of the design of different buildings or environments. The second one is to categorise different people according to their psychological and physical attributes to see the details of their reactions according to their own preferences using the affordance concept.

CRediT authorship contribution statement

Sajjad Hassanpour: Conceptualization, Methodology, Software, Validation, Writing – original draft. **Amir Abbas Rassafi:** Software, Validation, Writing – review & editing, Data curation. **Vicente A. González:** Visualization, Supervision, Writing – review & editing. **Jiamou Liu:** Formal analysis, Writing – review & editing.

Declaration of competing interest

None.

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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