



Agent-Based Simulation for Pedestrian Evacuation Behaviour Using the Affordance Concept

Sajjad Hassanpour^{✉a} and Amir Abbas Rassafi^{✉a}

^aFaculty of Engineering, Imam Khomeini International University, Qazvin 34148-96818, Iran

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ABSTRACT

Simulation modelling is a necessary tool to analyse pedestrian movement behaviour in order to predict the social and collective behaviour in different situations. Psychological aspects of human behaviour in interacting with the environment is the critical point in the pedestrian simulation context. The affordance theory originated from psychology and humanities is a key concept to address this issue and model the relationship between an agent and his/her environment. This study aims to introduce a prototype of an agent-based model using the affordance concept to simulate the decision-making process during an evacuation. The proposed approach was tested to model the behaviour of evacuees in a platform of a subway station through both normal and emergencies. The results of the test including the evacuation time and flows toward different scenarios, showed that the model can work properly. The proposed approach can yield a useful tool for designers to mention pedestrian movement behaviour in their building designs.

1. Introduction

Predicting human behaviour in different situations was always one of the most complex issues that scientists and researchers have ever confronted. This complexity is due to the simultaneous consideration of physical and psychological dimensions. Today, simulation of human behaviour is turning to a crucial necessity in public and social system design such as designing public transportation infrastructures. Knowing the human preferences to move toward a path or in a building becomes even more vital when considering particular situations like emergency evacuations due to a terrorist attack, fire, natural disasters, or other emergent incidents. There are numerous examples of crowded catastrophes by human stampede all around the world. Therefore, researching in this area can be so useful not only to optimise the space design of transportation infrastructure but also to reduce the loss of lives.

This paper tries to present a novel agent-based simulation of pedestrian evacuation from a platform of a subway station to evaluate the evacuation time and quality toward different scenarios. To model the interactions between agents and the environment considering the social behaviour dimensions, the affordance concept was used. Also, it examines the empirical

emergency evacuation capacity of exit areas, which is defined as the maximum flow of pedestrians that can pass the exit during a predefined period of time (Cheng and Yanga, 2012). The simulation codes and interfaces of the approaches were specifically developed within the NetLogo software environment (Wilensky, 1999), which is a free multi-agent programmable modelling environment.

2. Literature Review

Pedestrian simulation models generally can be categorised into three types concerning the goal of the simulator; macro-simulation, mesoscopic simulation, and micro-simulation level. Each level considers more details of the crowd respectively. Agent-based modelling (ABM) is one of the most popular micro-simulation approaches to use classical and constructive mathematics for social sciences (Borrill and Tesfatsion, 2010). It is a useful tool to derive the dynamic behaviour of a complex system from studying individual agents who make up the system (Railsback and Grimm, 2011). Vizzari et al. (2012) try to use ABM for reaching a better representation of pedestrian groups and the aggregate interaction (Vizzari et al., 2012).

A representative concept is social force model where the

CORRESPONDENCE Sajjad Hassanpour ✉ sajjad.hasanpour@gmail.com Faculty of Engineering, Imam Khomeini International University, Qazvin 34148-96818, Iran

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interaction between agents as attracting and expelling forces, attracting force to a wall, following tendency to a leader and various specific situations can be considered (Helbing and Molnar, 1998). Another idea is Cellular Automata (CA) model where space is discretized 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, Chen et al. (2019) developed a cellular automaton model on social forces interaction in building evacuation (Chen et al., 2019).

In ABM, the interactions between agents (social interaction) play an important role. In this kind of simulation model, we deal with an environment that contains both objects and agents that are assumed as autonomous entities. The agents will be able to interact with each other inside a multi-agent system. However, the construction of movement rules and agent's interactions should be inspired by the observation of the real world (Pluchino et al., 2014; Liun et al., 2016). The ABM is suitably used to model the occupants' behaviour in a building (Liao et al., 2012). Being able to integrate dynamic physics, computer science, biology, transportation, and social science make ABM a strong tool in representing pedestrian movement, simulation and visualisation (Tang and Hu, 2017). Several studies used NetLogo software as a reliable platform to apply agent-based simulations in different areas, especially for pedestrian movement (Bandini et al., 2009; Luisa et al., 2011).

2.1 Evacuation

Evacuation from buildings or public places has always been one of the most important safety factors for managers of transportation systems. In recent years, many studies have been conducted on this issue (Vorst, 2010; Huo et al., 2014; Liun et al., 2016; Serulle and Cirillo, 2017). ABM was used to model the behaviour of a human in special situations such as evacuation under terrorist attack (Ma et al., 2016).

When facing an emergency, the main goal is being safe while the decision making of the agents is the key issue to reach this goal. The ABM in a cellular framework is used to model the post-earth-quake evacuation mechanism (Song et al., 2019). The decisions depend directly on the effects of environmental and social factors (Lovreglio et al., 2016a, 2016b; Cao et al., 2019). The presence of fire, smoke, or any dangerous elements, general availability of the path to the exit, visibility condition, and the distance from the exit gate are some effects of the environment; the interaction of the evacuees and their flow are the social factors, which were mentioned in this study. Their model also showed a high degree of behavioural uncertainty through the decision-making process.

Some researchers have tried to model human behaviour using discrete choice models in evacuation literature. The choice between co-located stairs and escalators in transit stations was modelled dynamically using binary and mixed-logit models (Srikukenthirana et al., 2014). Haghani et al. (2014), also searched for important factors affecting the exit choice of pedestrians and those should be considered during building evacuation by a new

data collection method called "stated preferences off revealed preference" (Haghani et al., 2014).

Zou et al. utilized the ABM to develop a prototype of a simulation model for pedestrian dynamics in the subway station using NetLogo software. They have done nice work to make the simulation as realistic as possible, yet they missed the psychological aspects of human behaviour during evacuation (Zou et al., 2019). The panic theory proposed by Quarantelli in 1954 can be a good approach to model the anxiety of people, however, later, some studies argued that despite the impact of stress people make rational decisions in building emergencies instead of losing self-control (Quarantelli, 1954; Johnson, 1987; Fahy and Proulx, 2009).

2.2 Affordance Concept

The affordance concept, which originates from psychology and humanities, was used for the first time by Gibson in 1977 to model the interaction between agents and the environment. He stated that "each element in the environment can provide a service for an agent to do an action whether for good or ill due to its properties" (Gibson, 1977). It was the beginning of using this concept to model human behaviour considering his/her perceptions from their observations in the environment before decision-making. Afterwards, the affordance concept became a popular tool for researchers and scientist in several areas in which interaction is the key point (Kim et al., 2011; Jonietz et al., 2013; Joo et al., 2013; Ksontini et al., 2014; Patil, 2014; Busogi et al., 2017).

Patil (2014), in his dissertation, used the affordance concept as a tool for the path prediction model, which provides an opportunity to observe human behaviour in social activities such as migration (Patil, 2014).

Klügl (2016) developed an affordance-based approach to capturing the interactions in ABM. This study initially showed why and how affordance could be used in modelling interactions and finally illustrated the approach to after-earthquake behaviour (Klügl, 2016). Joo et al. (2013) used this concept to simulate agent behaviour in an emergency evacuation. They used affordance in a cellular environment in which the agent dynamically makes his/her decision to choose the best cell in their perceivable boundary through a warehouse fire evacuation problem (Joo et al., 2013). Busogi et al. (2017) introduced "weighted affordance-based agent modelling" as a tool to address the physical and psychological dimensions in dynamic agents' decision-making process (Busogi et al., 2017).

The affordance concept also has been used to simulate space occupation process for road traffic flow (Ksontini et al., 2014). The study showed how this concept could be used to propose a more realistic model to identify the possible space occupation actions afforded by the environment and by other agents.

In this paper, we are seeking to simulate the details of pedestrian movement behaviour considering their preferences in wayfinding during evacuation. Therefore, using the affordance concept in an agent-based framework to model the human

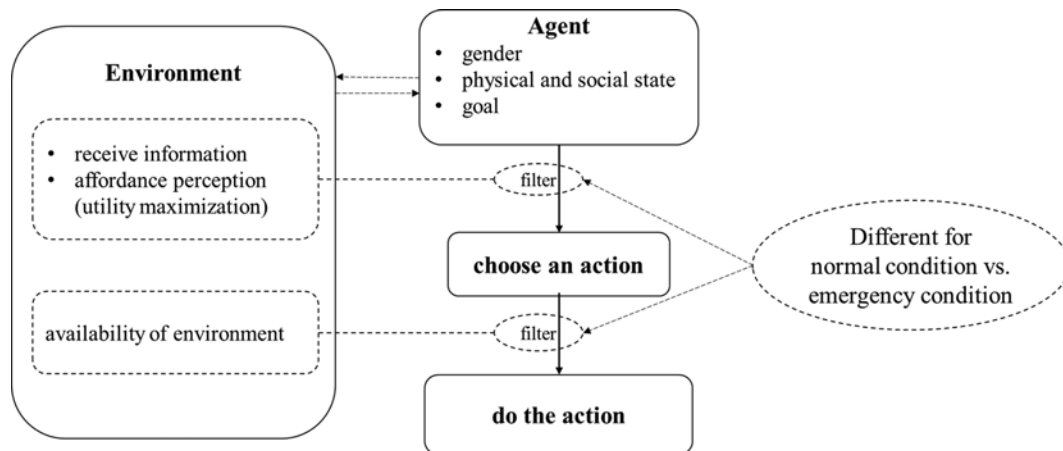


Fig. 1. A General Framework of Agent's Decision-Making Process

preferences instead of using a classic rule-based ABM can lead to a novel fruitful approach in this context.

3. Modelling Approach

We are dealing with a rational agent who thinks before deciding the heading and the speed of his/her movement at each moment. The decision-making process in an agent directly depends on the environment. Fig. 1 shows the general operation of the decision-making of an agent who interacts with his surrounding environment. We assumed a cellular environment as near as possible to a real case. The patch (a grid cell) size is defined due to the standard pedestrian space for occupancy, which is a square of 60 cm × 60 cm (HCM, 2010). Notice that the cells may contain more than one agent when agents may stand in the way that they occupy a portion of the cell space, but two agents cannot be at the same point (rule-based collision avoidance) (Liu et al., 2015). The decision-making process will occur in a cellular approach while moving is not essentially cellular as the agents can move different distances according to their different characteristics. At each moment, all the agents intend to move toward their goal through the best possible path. The best path is the cell which contains the highest amount of affordance among the agent's neighbourhood patches at each moment.

The extended Moore neighbourhood approach was used in this paper. Fig. 2 shows the extended Moore neighbourhood for $r = 3$. The amount of r of the extended neighbourhood depends on the speed of the agents at that moment. So, each agent has his/her specific neighbourhood cells according to his/her physical ability. The grey area in Fig. 2 shows the agent's neighbourhood which is used to calculate the amount of crowd toward the selected cell.

$$r := \text{Roundup} \left(\frac{\text{speed}}{0.6} \right) \quad (1)$$

We will discuss the term speed later, but to explain it in a nutshell, by speed here, we mean the speed which the agent has when there is no barrier, obstacles, or any other agents ahead

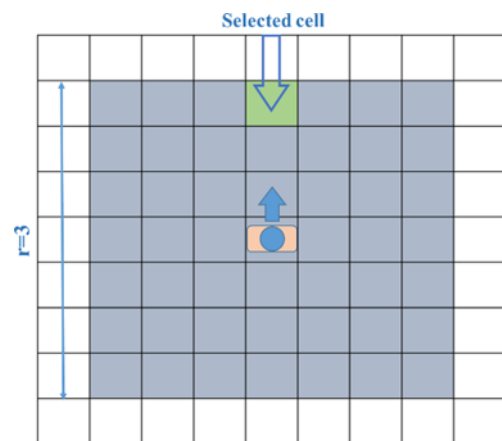


Fig. 2. The Moore Neighbourhood ($r = 3$)

(free flow walking speed) (Rahman et al., 2012).

An agent can face one of the cells within his neighbourhood based on the affordances they present. Each affordance which a patch presents can change the amount of utility that an agent gains. Therefore, each cell has as many affordances as the number of goals defined for agents. Fig. 3 shows an agent who is standing at the cell y and intends to reach the goal i . If aff_{ij} is the amount of affordance of a neighbour cell j for the goal i , around the cell y that an agent stands on, the agent chooses a cell that leads to the highest utility among the neighbours. The number of cells in the Moore neighbourhood of range r is the odd squares $(2r+1)^2$.

Let us assume the chosen cell is the neighbour cell $j = 3$ in Fig. 3, which will change the amount of his utility from $U1$ to $U2$. This procedure continues until the agent reaches his goal where his utility will be maximum (minimum disutility). So, at each time step t , the agent chooses his optimal patch (best patch) that minimises his disutility amount (the patch with the highest affordance).

The variables by which the amount of affordance is derived at each time step for a cell include the distance from the goal,

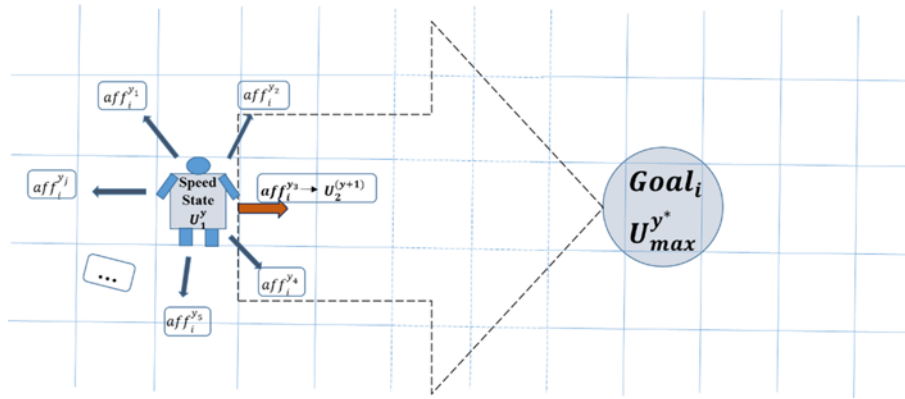


Fig. 3. The Possible Moving Choices for an Agent and the Affordances of Surrounding Patches

danger, and crowd. An agent rationally tries to get close to his goal cell as much as possible in each step. In the path to the goal, everyone tries to choose a less crowded direction. The agents also avoid the danger that can be the fire or smoke around the environment cells (Lovreglio et al., 2016a).

According to the factors mentioned above, an affordance is defined for each patch and is dynamically updated after each time step. The negative utility can be literary considered as disutility so that the agents will choose the smallest negative amount. Therefore, it can be interpreted that the agents are trying to minimise their disutility as they are maximising the affordance amount.

$$aff_{iu}^{y_i} = -\alpha \cdot Dis_i^{y_i} - \beta_{\mu} \cdot D^{y_i} - \gamma_{\mu} \cdot Cr^{y_i} \quad (2)$$

where

$aff_{i\mu y_t}$ = The affordance amount of patch y toward goal i at the time step t for an agent type μ

Cr_{y_t} = The crowds or congestion toward the patch y at the time t (number of people inside the sight of the agent when he faces the selected cell-blue area in Fig. 2)

$Dis_{i y_t}$ = The distance between the y patch and goal i at time t

D_{y_t} = The amount of danger existed in the patch y at the time t (it can be different according to the emergency condition type. For example, it can be fire or non-structural damage caused by an earthquake)

α, β, γ = The weights of each variable according to the agent preferences ($\alpha + \beta + \gamma = 1$)

To simplify the calculations, we assume that there are three types of agents with the following order of preferences:

Type 1 ($\mu = 1$) who prefers to go through the nearest path: $\alpha = 0.5, \beta = 0.25, \gamma = 0.25$

Type 2 ($\mu = 2$) who prefers to go through the safest path: $\alpha = 0.25, \beta = 0.5, \gamma = 0.25$

Type 3 ($\mu = 3$) who prefers to go through the uncrowded path: $\alpha = 0.25, \beta = 0.25, \gamma = 0.5$

As we have three types of agents ($\mu = 1, 2, 3$) and three goals ($i = 1, 2, 3$) defined in the simulation model, we will have $9(3 \times 3 = 9)$ different affordances for each patch of the environment

that should be updated at each time step t . Consequently, at each time step, all the agents try to choose one of their neighbour patches with the highest amount of affordance due to their character and goal. The final step of this phase is checking the availability of the chosen patch, which depends on whether it is already totally occupied or not.

One of the principle variables which reflects human behaviour during an evacuation is the agents' speed. This paper uses two kinds of speed for an agent. The first speed is the maximum ability of the agent to move, which he can have this speed in a free flow situation and without any disturbance. The second one is the speed he actually has when he is within the simulation environment, among other agents and the walls. For the first kind, we assign the potential speed to the agents based on the real data observation, and the second speed depends on the situation at each time steps and the rules we define later.

Observation in the platform of a subway station in Iran showed that in the normal situation the average walking speed for the people who are walking through platform waiting for the train (when there is no congestion or any barrier) is 0.6 (m/s), which is slightly lower than the average normal speed of 1.2 m/s (HCM, 2010).

The speed of these people increased when the train enters the platform tunnel to 1.5 m/s. For the people who get out of the train, this amount is nearly equal to 1.1 m/s. In the emergency, these speeds reach 2.5 (m/s) (Zebala et al., 2009; Zębala et al., 2012). It has been shown that the speed of pedestrian follows a normal distribution in which the average speed of men is slightly larger than that of women (Huang and Ma, 2010).

In order to simulate speed in NetLogo software, we should use patches and movement distances. As discussed earlier, each patch is 0.6×0.6 m; So, when an agent moves a complete patch in a single time step (which is one second), his speed is 0.6 m/s. Accordingly, when the agents are walking with the speed of 1.8 m/s he/she can pass three cells in each second ($r = 3$).

$$\begin{aligned} & 3 \text{ (number of cells)} \times 0.6 \text{ (length of each sell)} \\ & = 1.8 \text{ (total passed length)} \end{aligned} \quad (3)$$

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 0.6. Pay attention that this speed is the speed that the agent uses when there is enough valid space ahead. If there is any barrier in front of the agent (such as other agents), at each time-step, he will reasonably move to the available distance, which leads to a speed lower than his assigned potential speed. The stopping criteria and the assumptions (rules) are discussed in the following sections.

4. The Test: Shahed Subway Waiting Platform

Although this study is as a prototype of a simulation approach, we tried to investigate a real subway platform to have better realistic results in our test. Therefore, we chose one of Tehran subway stations called Shahed. This station was selected because it is a typical subway station in Tehran and has a considerable volume of both exiting and entering the platform because it is located in the south end of line 1 Tehran subway. The waiting platform length is 145 m, and its width is 5 m. It has two entrance/exit areas with a length of 4.5 m from where the passengers come and go to the platform.

Gathering some initial data by watching the films captured from the platform cameras, we provide the initial quantitative variables such as inter-arrival times ΔT , number of female against the male, mean free flow walking speed of different people, and train headways, speed, and delays.

Emergency Evacuation Capacity (EEC), which is defined as the maximum flow of pedestrian evacuating from the exits in a given time (10 seconds in this study), is used as an indicator to evaluate the exit width. The maximum evacuation flow (MEF) in the emergency condition is examined for different scenarios (two exit widths (1.5 and 3) and different numbers of doors (1, 2, 3, and 4)). Then it is investigated if we can estimate empirical EEC from MEFs.

The evacuation time is another indicator that can describe the quality of a platform which can truly show the efficiency of the physical characteristics of a platform, especially in an emergency.

The total time needed by all agents to get out of the platform in the emergency condition is considered as total evacuation time (TET).

For verification and validation of the model, the basic requirements derived from the literature have been tested (Lubaś et al., 2014). Qualitative basic tests including reasonable movement and navigation, pedestrians' ability to maintain assigned walking speed or avoiding boundaries (walls), social interactions, and choosing the best direction toward the exit doors have been successfully passed.

4.1 Normal Situation (Non-emergency)

In a non-emergency situation, all people at the platform are involved in commuting by the subway, coming in, going out, getting on/off the train or waiting for the train to get on. Fig. 4 presents the interface of the simulation model in NetLogo and the variables, which can be controlled by the modeller.

Poisson distribution is a reasonable assumption for the random entrance of people to the waiting platform; so, the inter-arrival times (ΔT) have an exponential distribution with a mean value for ΔT that is expressed in seconds and can vary during the day.

The attributes of each agent will be stochastically assigned to it right after its generation by using probability distribution. The normal distribution often works for a general explanation for the potential speed of pedestrians (Huang and Ma, 2010).

A standard deviation of 0.15 was used for the speeds where the mean values and other approximations for speed changes were chosen by watching the real platform from station cameras. The speed calculation, for instance, was done by recording the time it took people to pass two predetermined points at the platform.

$$S = \frac{\sum_{i=1}^N t_i}{N} \quad (4)$$

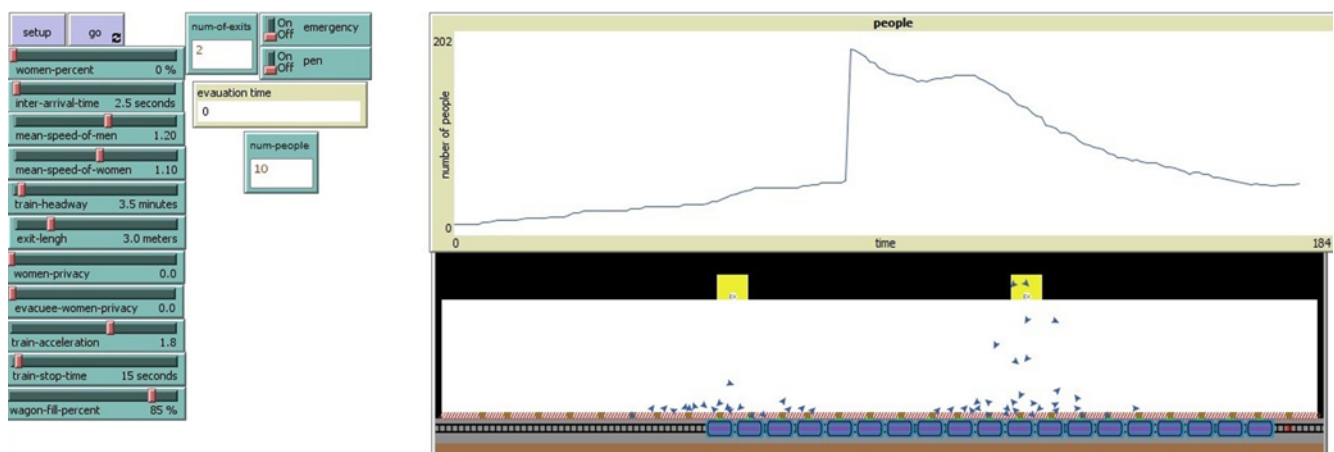


Fig. 4. Operational Interface in NetLogo

where

- L = The distance between two predetermined points in the platform that can be observed clearly from the cameras
- N = Number of people observed to evaluate the mean speed
- S = A reasonable approximation for the mean speed of agents
- t_i = The time took by the person i to pass the L

Each agent occupies an equal space of a complete cell (patch size = 60×60 according to (HCM, 2010) at each time unit. However, the cell occupation can vary for different kinds of agents due to their physical attributes. This issue is one of the limitations of this study which can be studied in future researches. In this study, it is assumed that all the agents occupy the same space of cells.

Figure 5 illustrates the general flowchart of the normal situation, which shows the process of agents moving toward their goal in each time step. An agent observes his surrounding area first, then he heads to the best available cell, and, finally,

moves toward the chosen cell base on his specific attributes such as potential speed. The whole process reminds us of the main framework of Belief, Desire, and Intention (BDI) architecture. The agents initially find the information and create their belief set by observation. Then they define their desired goals and try to choose the best one based on their beliefs. 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 (Norling, 2004). The whole moving process can be explained in a framework based on the following assumptions:

1. All agents can observe their surrounding cells (no one is disabled or blind), but their preferences through the affordances of the different cells may differ (different perceptions).
2. Each step of a movement should lead to an increase in the amount of agents' utility. Therefore, they choose from the neighbour patches whose affordances are higher than the cell they are standing on.
3. At each time-step, agents will move according to their predefined specific potential speeds and the available space

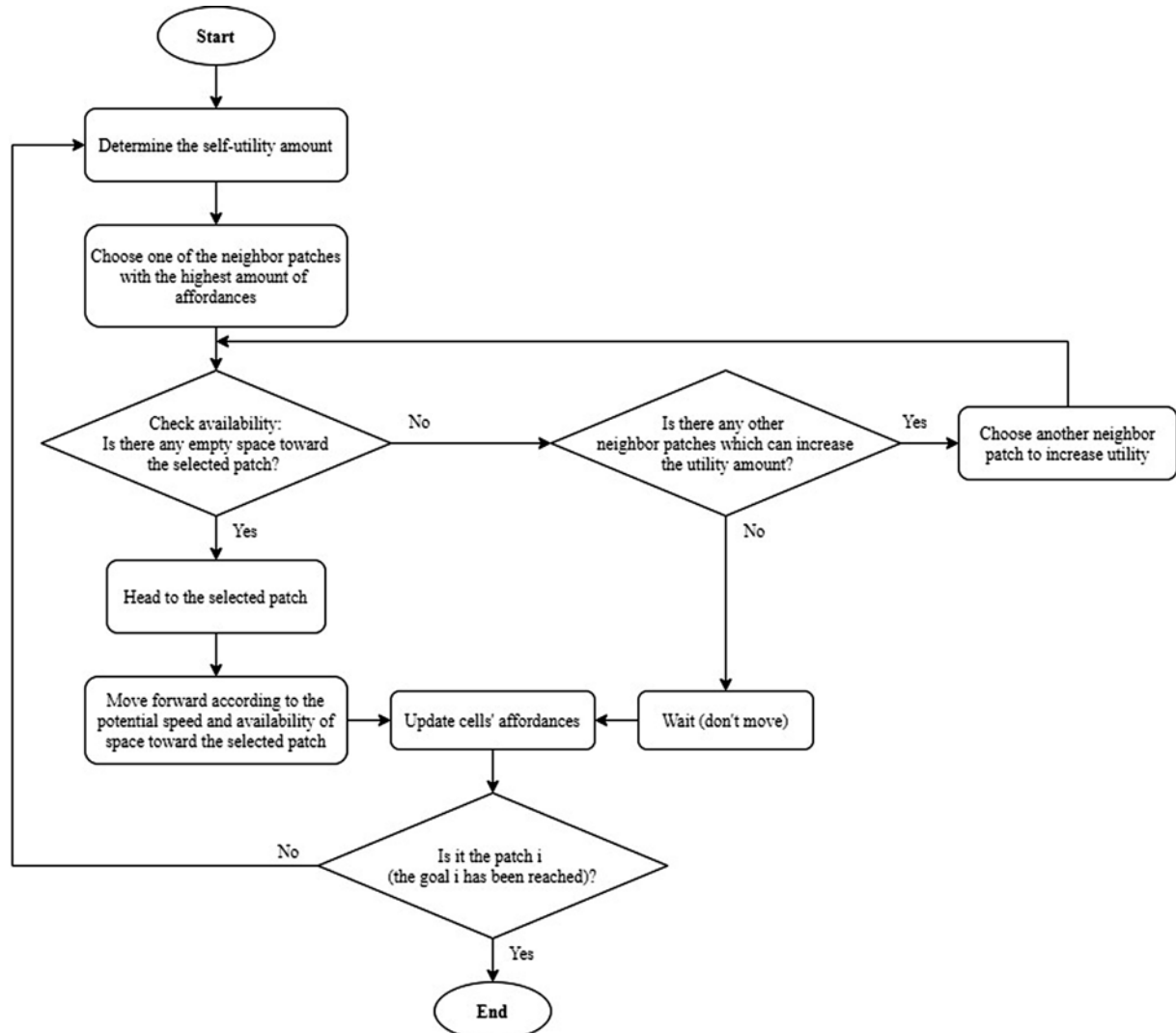


Fig. 5. The Flowchart of Normal Situation Simulation in a Subway Platform

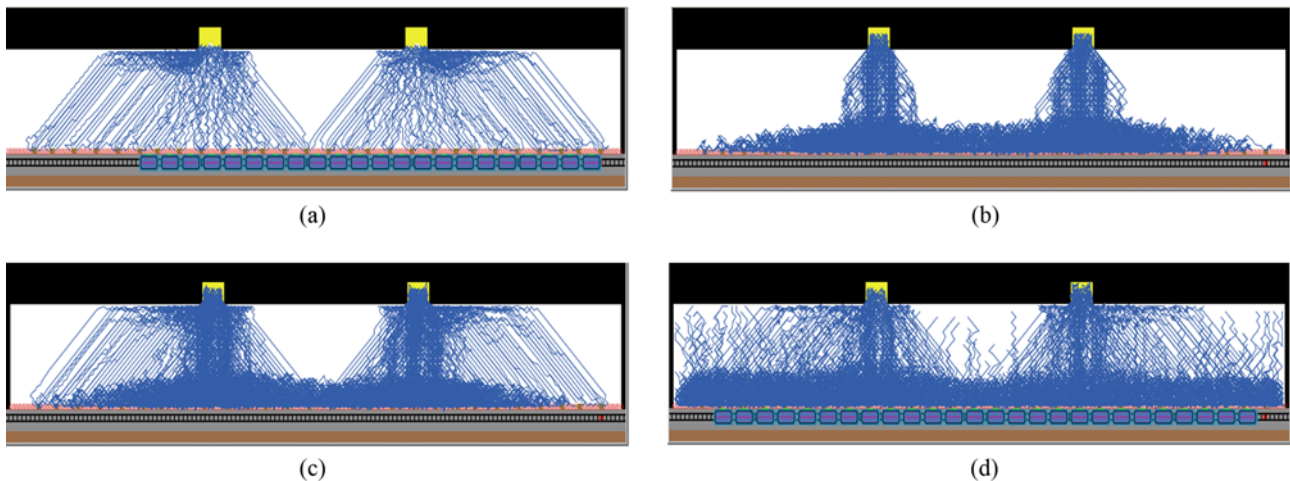


Fig. 6. Movement Traces through Different Scenarios: (a) Just People Who Get Out of the Train and Go Out to the Exits, (b) Just People Who Enter to the Platform and Go For the Train, (c) Both People Who Enter and Get Out, (d) All Movements in a Platform in Normal Condition

in front of them.

4. If there is not any suitable patch that leads to higher utility, the agent waits for one time-step.
5. The availability of a chosen patch depends on whether the whole path toward the selected patch is completely occupied by other agents or not.

4.1.1 Results for Normal Condition

Figure 6 shows the overall patterns of three different groups of movements separately and mixed. The first group includes people who get out of the train to go out of the platform through the exits. The second group belongs to people who enter the platform and want to travel by train. The third group belongs to the ones who are scattered all over the platform just waiting for some time in the station may be to meet someone. The figure shows the spaces which are used more by people during their movements.

Figure 7 shows the number of people at the platform through a period of time for different average inter-arrival times of entrance (0.5, 1, 2, 3, 4, and 5 persons per second) and different headways (5, 8, and 10 minutes). The figure presents simulation for the normal situation for a typical standard platform with two entrance/exit areas with a width of 4.5 m. The results are shown for at least three loops of a train coming.

The jump in the graphs is the point at which the trains open their doors, and the passengers get in and off the train. It can be seen that when the inter-arrival times of passengers to the

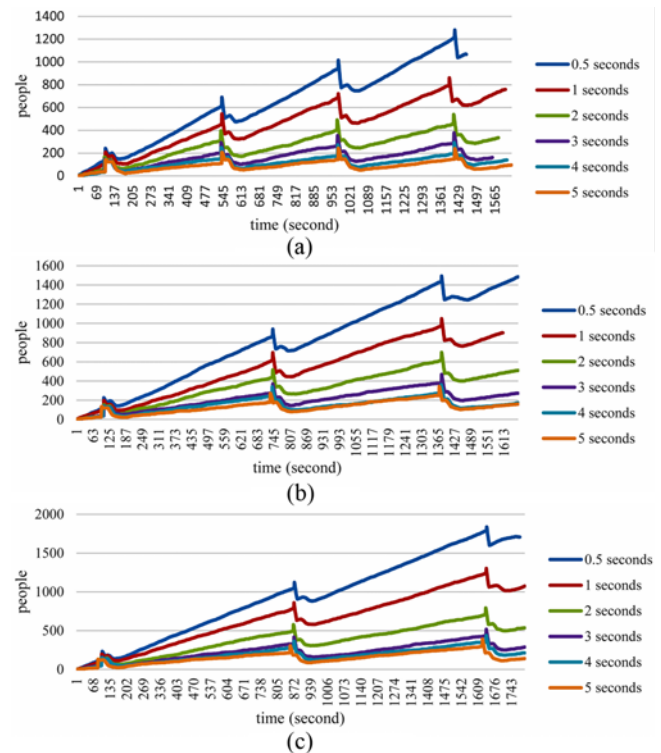


Fig. 7. The Line Charts of People Movement in the Simulated Platform for Different Train Headways and People Inter-Arrival Times: (a) Headway = 5 Minutes, (b) Headway = 8 Minutes, (c) Headway = 10 Minutes

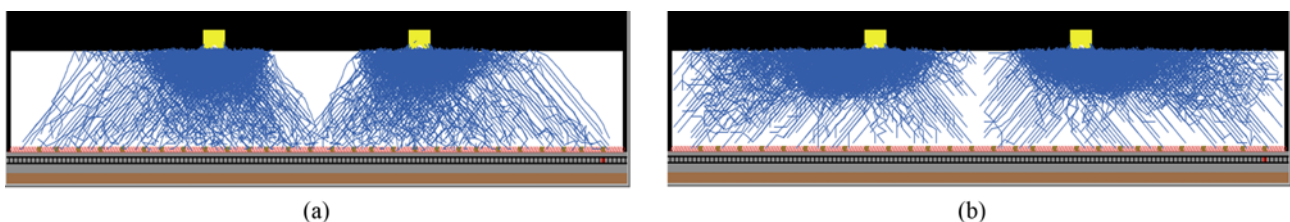


Fig. 8. Movement Traces through Evacuation Process: (a) People Emergency Evacuation Right after They Were near Edges Waiting for Train Entrance, (b) People Evacuation when They Are Scattered All over the Platform

platform are less than 2 seconds, the rate of people coming to the platform will be more than the rate of people exiting; so eventually it will be a failure in congestion if this rate of arrival continues. Knowing the maximum number of agents that platform can accommodate (i.e., 2,500 in the simulated model), we can find out the time when the failure happens.

4.2 Emergency

Figure 8 shows different movement traces of people evacuating from the platform. The first part of the figure includes people who are waiting for a train at the edge part of the platform, and suddenly the emergency condition happens. The second part shows the emergency evacuation when people are scattered all over the platform. The spaces which are used more by people are clearly darker than the less-used spaces.

This evacuation may be due to different reasons such as an explosion, fire, terrorist attack, etc. If we intended to simulate all the details of physical events, we had to simulate the reason for evacuation as well; however, in this study, we want to focus only on the people evacuation process. The assumptions for this condition are as follows:

1. No train will move or enter the station
2. No people will enter the platform
3. The people try to evacuate the platform as soon as possible, so they reasonably choose the nearest exit door. Their potential speed will be higher due to their predefined specific attributes in emergency.
4. If there is not any suitable patch that leads to higher perceived utility, the agent waits for one time-step and repeats the process after the updates of the cell until the goal is reached.
5. The availability of a chosen patch depends on whether the

whole path toward the selected patch is completely occupied by other agents or not.

The affordance of each cell will be different in an emergency, as the goal patch has been changed for all agents. The goal patch will be the nearest exit door for each agent.

The empirical pieces of evidence reasonably suggest that in the case of an emergency evacuation, emotional reactions tend to blur perception and fuel panic responses among agents. To consider this issue in the models in the affordance function, the distance effects will become dominant.

4.2.1 Results for an Emergency Condition

In an emergency condition, we tested the pedestrian evacuation

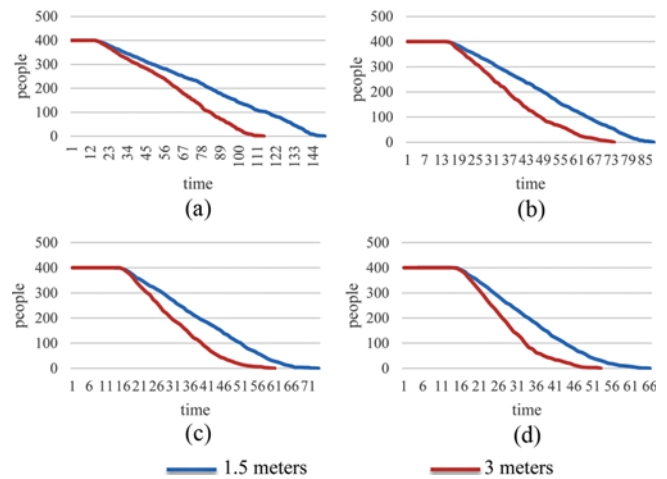


Fig. 9. The Evacuation Line Charts for the Simulated Platform for Different Number and Size of the Exit/Entrance Area: 1 Door, (b) 2 Doors, (c) 3 Doors, (d) 4 Doors

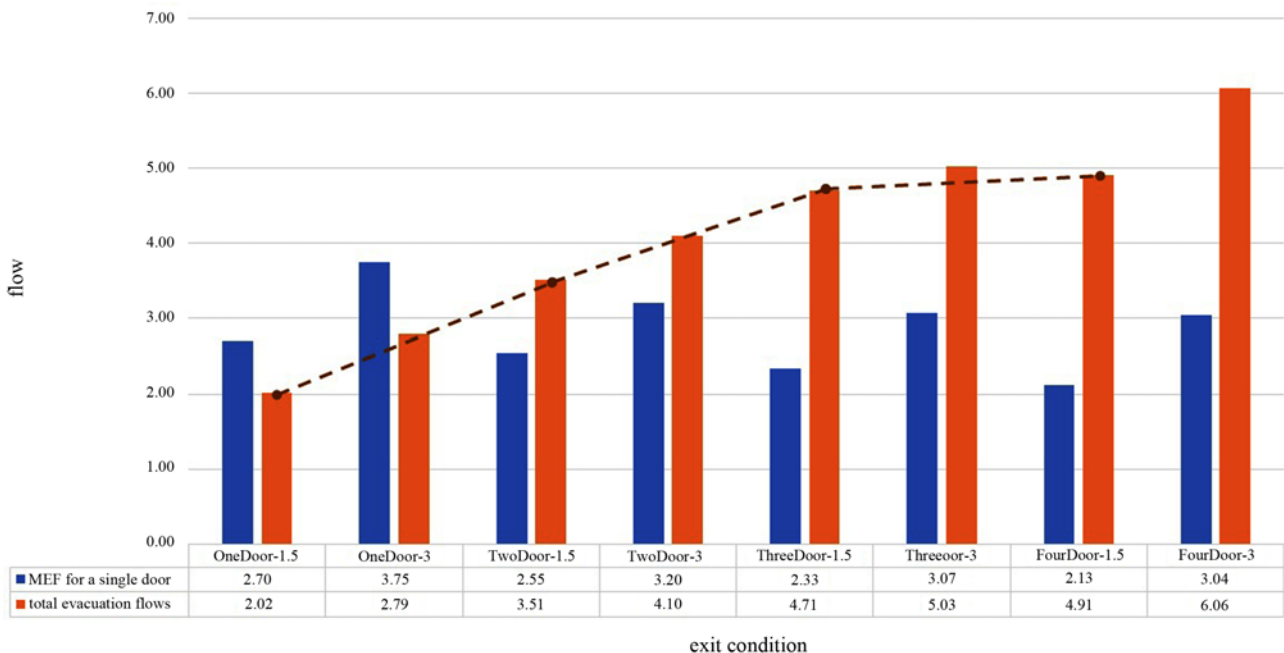


Fig. 10. EEC and Total Evacuation Flow for Different Exit Conditions

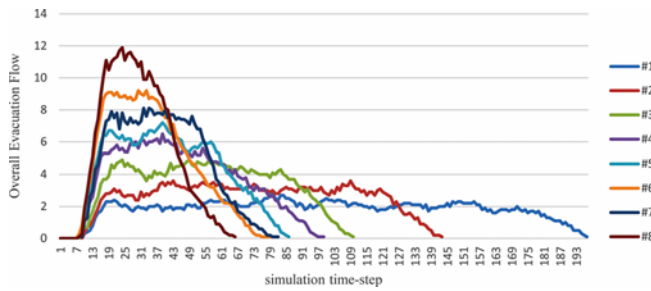


Fig. 11. Overall Evacuation Flow of Different Scenarios

flow through different scenarios in which the number and sizes of exits were different. The model has been run 4 times for each scenario (the total number of replications: $8 \times 4 = 32$) which led to satisfactory estimations of the mean value for the dependent variables (evacuation time and flows). Table 1 shows the different scenarios' conditions and overall statistics of simulation replications.

Figure 9 illustrates the evacuation of 400 people in emergency condition for a different number of exit doors and two different lengths of exists (1.5 and 3 m). The vertical axis of the charts shows the number of people, and the horizontal axis is time (seconds). To have more realistic results, we run the model at the normal situation for 10 seconds, followed by turning it to the emergency condition; that is why there are horizontal parts at the beginning of curves before the fall.

As can be seen from Fig. 9, the curves are turning from a linear graph into a quadratic polynomial at the end. The quadratic parts are increased by a number of exits and their width. It can be interpreted by the slow potential speed of some people who reach the exits later when others already evacuated.

So, the slope of the linear part should be calculated as the evacuation flow of exit areas.

The maximum flow of people evacuating from the platform was investigated in order to find the empirical capacity of the exit areas of the platform. Although the flows were calculated in 10 seconds, the unit of MEF is person per second. Therefore, the total number of peoples evacuated in 10 seconds will be divided by 10 to calculate MEF. Fig. 10 shows the total evacuation flows and MEF for one door both in one chart for different exit conditions. As it was expected, the MEFs are the same for constant physical condition (same width). That is because the capacity is a function of physical attributes of infrastructure. So we can see the MEF for exit doors with 3-meter width is higher than the 1.5-meter doors.

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 total evacuation capacity of the platform, which is approximately 2.7 and 3.75 for 1.5 and 3-meter width, respectively.

Designers or managers can use the results to decide on the physical attributes of the infrastructure and efficiency of the evacuation process. Paying more attention to figure 10, the dashed line depicts total evacuation flow for different numbers of doors with the same width of 1.5 meters. The slopes of the line from 3 exits to 4 exits are approximately the same (nearly horizontal line). It can be interpreted that for the 1.5-meter size of the exit door, there is no need to have more than three doors. Also, we can see that three doors with a width of 3 meters work even slightly better than four doors with a width of 1.5 meters. Also, Fig. 11 confirms this issue where the curve of the flow for scenario#6 (3 doors with a width of 3 meters) better evacuation overall flow in comparison with the flow for scenario#7 (4 doors

Table 1. Overall Descriptive Statistics of All Door Conditions

Number of doors	Width of doors (meters)	Scenario	MEF		TET	
			Maximum evacuation flow		Total evacuation time	
			Mean (person/second)	S. D.	Mean (second)	S. D.
1	1.5	#1	2.7	0.14	119	0.85
	3	#2	3.75	0.21	86	0.42
	Total		3.23	0.52	102	18.88
2	1.5	#3	5.1	0.28	68	3.39
	3	#4	6.4	0.14	58	1.28
	Total		5.75	0.77	63	6.09
3	1.5	#5	7	0.28	51	0.85
	3	#6	9.2	0.15	48	0.42
	Total		8.1	1.28	49	1.98
4	1.5	#7	8.5	0.57	49	0.42
	3	#8	12.15	0.35	40	0.15
	Total		10.33	2.14	44	5.37
Total	1.5		5.83	2.33	72	30.16
	3		7.88	3.35	58	18.79
	Total		6.85	2.98	65	25.3

Table 2. The One-Way ANOVA Results for the Dependent Variable according to the Factor of the Numbers of Doors

Dependent variables		Sum of Squares	df	Mean Square	F	Sig.
MEF for one door	Between groups	.944	3	.315	1.249	.335
	Within groups	3.022	12	.252		
	Total	3.966	15			
Total MEF	Between groups	111.955	3	37.318	20.689	.000
	Within groups	21.645	12	1.804		
	Total	133.600	15			
Total time	Between groups	8,319.497	3	2,773.166	26.009	.000
	Within groups	1,279.485	12	106.624		
	Total	9,598.982	15			

Table 3. One-Way ANOVA to Compare TET between Different Numbers of Exit Doors

Dependent variable	(I) door	(J) door	Mean difference (I-J)	Std. Error	Sig.	95% Confidence interval	
						Lower bound	Upper bound
Total time	1	2	38.99500	7.30150	.001	17.3176	60.6724
		3	53.09250	7.30150	.000	31.4151	74.7699
		4	58.19500	7.30150	.000	36.5176	79.8724
	2	1	-38.99500	7.30150	.001	-60.6724	-17.3176
		3	14.09750	7.30150	.267	-7.5799	35.7749
		4	19.20000	7.30150	.089	-2.4774	40.8774
	3	1	-53.09250	7.30150	.000	-74.7699	-31.4151
		2	-14.09750	7.30150	.267	-35.7749	7.5799
		4	5.10250	7.30150	.896	-16.5749	26.7799
	4	1	-58.19500	7.30150	.000	-79.8724	-36.5176
		2	-19.20000	7.30150	.089	-40.8774	2.4774
		3	-5.10250	7.30150	.896	-26.7799	16.5749

Table 4. Tests of between-Subjects Effects for the Dependent Variable of TET

Source	Type III sum of squares	df	Mean square	F	Sig.	Partial eta squared
Number of doors	8,319.497	3	2,773.166	1,466.687	.000	.998
Width	761.622	1	761.622	402.811	.000	.981
Number * width	502.737	3	167.579	88.630	.000	.971
Error	15.126	8	1.891			
Total	7,6932.745	16				
Corrected total	9,598.982	15				

a. R Squared = .998 (Adjusted R Squared = .997)

with a width of 1.5).

We also conducted some statistical analysis for different scenarios. Table 1 shows the overall descriptive statistics (values of the mean and standard deviation) of two dependent variables- total maximum evacuation flow and total evacuation time- in different scenarios with different exit conditions.

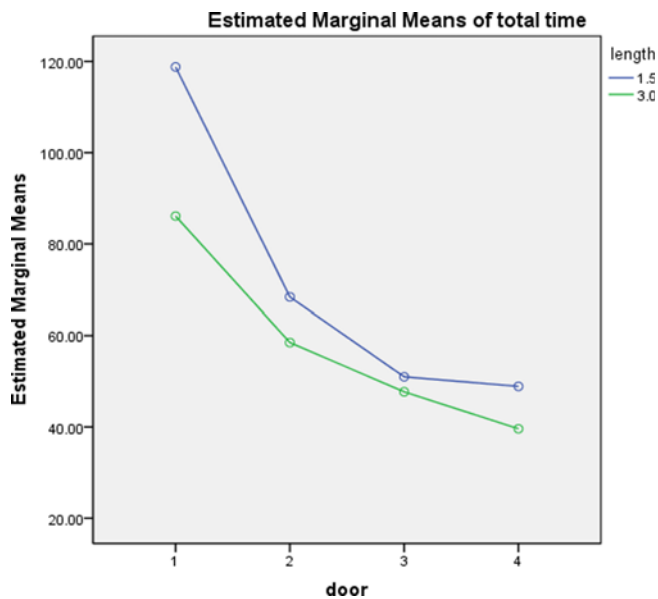
To see the impact of the numbers of doors as we have for different groups for the numbers of doors, once we conducted one-way ANOVA to compare the means of dependent variables (TET and MEF), neglecting the impacts of widths. The Levene Test confirmed the assumption of homogeneity. Table 2 shows

the results of ANOVA comparing the numbers of doors effects for different dependent variables. The numbers of doors definitely affect the TET, and total evacuation flows ($F = 26.009$ and $F = 20.689$ respectively and p-values are less than 0.05 for both), but the means are not significantly different for maximum evacuation flows of one door ($p = 0.335$). It completely makes sense as the MEF supposed to perspective the capacity of doors and it depends on the physical attributes of the doors.

Table 3 shows the multiple comparisons between the groups. It can be seen that there is a significant difference in TET between 1 door and other numbers of doors, while this amount is

Table 5. Comparisons between Internal Groups of the Number of Doors Regarding TET

	(I) door	(J) door	Mean difference (I-J)	Std. Error	Sig.	95% Confidence interval	
						Lower bound	Upper bound
Tukey HSD	1	2	38.9950	.97231	.000	35.8813	42.1087
		3	53.0925	.97231	.000	49.9788	56.2062
		4	58.1950	.97231	.000	55.0813	61.3087
	2	1	-38.9950	.97231	.000	-42.1087	-35.8813
		3	14.0975	.97231	.000	10.9838	17.2112
		4	19.2000	.97231	.000	16.0863	22.3137
	3	1	-53.0925	.97231	.000	-56.2062	-49.9788
		2	-14.0975	.97231	.000	-17.2112	-10.9838
		4	5.1025	.97231	.003	1.9888	8.2162
	4	1	-58.1950	.97231	.000	-61.3087	-55.0813
		2	-19.2000	.97231	.000	-22.3137	-16.0863
		3	-5.1025	.97231	.003	-8.2162	-1.9888

**Fig. 12.** Estimated Marginal Means of TET for Different Scenarios

not significant between 2 and 3 ($p = 0.267$) or 3 and 4 doors ($p = 0.896$). So if we do not consider the width of doors (let us say the width is about 2 meters), we can say that it is not efficient to have more than two exit doors for the evacuation of 400 people (200 for each door) from the platform as the evacuation time will not significantly change. A similar result was reached in previous studies (Chen et al., 2016).

To see the interaction effects of the number and width of the exit doors, we conducted two-way ANOVA as well. Table 4 shows the between-subject effects for the dependent variable of TET which are clearly showing that the TET is highly affected by both the numbers of doors ($F = 1,466.687$ and $p < 0.05$), the width of doors ($F = 402.811$ and $p < 0.05$). Also, we have a significant interaction effect ($F = 88.63$ and $p < 0.05$). As it is shown in Table 5, the inter-group multi-comparison of the mean

value of evacuation flows between different numbers of doors showed significant differences between all the groups ($p < 0.05$ for all binary comparisons by Tukey test). The amount of p-value between 3 doors and four doors is slightly higher than the other cases ($p = 0.003$). We can find this more apparent in Fig. 12 where estimated marginal means of TET are not significantly changing from 3 doors to 4 doors (the slopes of the curves are decreasing especially for the 1.5-meters door).

5. Conclusions

In this study, we used a dynamic agent-based simulation model in which the affordance concept was used in the decision-making process to consider the psychological aspects of agents. Subway platform evacuation was simulated to get a suitable illustration of this model. We used NetLogo free software and coded all the model rules in this platform through two normal and emergency conditions.

The simulation successfully was conducted for both normal condition and emergency. In normal condition, the effort was made to find the pattern of people moving in the platform in different scenarios. The physical variables such as the doors' width and number were not examined in this condition as we aimed to seek the pattern of people coming and going to the platform. The inter-arrival times and train headways were the model's variables in normal condition. We identified the scenarios that lead to the failure of platform capacity by comparing the entering and exiting rates in given attributes of exit doors and other sizes in a subway platform. The results showed the effects of congestion on evacuation time.

In the emergency, we investigated the evacuation quality through different physical conditions of the platform exit. For each scenario, maximum emergency evacuation flow was calculated as a good perspective of the empirical emergency evacuation capacity of the platform. The results showed how the physical attributes of the exit area could affect the evacuation process.



Having three exit doors with a width of 3 meters can present more evacuation flow than 4 exit doors with a width of 1.5.

As it was a demonstration of a prototype simulation model of evacuation, some limitations should be noted. First, we assumed a general evacuation case while the proposed approach can be developed for different particular emergency conditions such as a terrorist attack or earthquake by changing the utility function accordingly. Second, it was assumed that there are three types of evacuees with different priorities; however, in future studies, the utility function can be calibrated by gathering real data using stated preferences questionnaires which can lead to more reliable simulation. Additionally, using the stochastic approach to choose the next step by the agents according to their perceived affordances can help the model to become even more realistic. Also, coupling the proposed model with other tools such as constructional tools (BIM) can lead to a useful tool for the internal design of buildings.

Acknowledgments

Not Applicable

ORCID

Sajjad Hassanpour  <https://orcid.org/0000-0001-8028-6237>
 Amir Abbas Rassafi  <https://orcid.org/0000-0002-3419-0194>

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