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The role of crowd behavior and cooperation strategies during evacuation

Azhar Mohd Ibrahim[1], Ibrahim Venkat[2], Philippe De Wilde[3], Muhammad Rabani Mohd Romlay[1] and Alala Bahamid[1]

Abstract

Crowd dynamics have constituted a hotspot of research in recent times, particularly in areas where developmental progress has taken place in crowd evacuation for ensuring human safety. In high-density crowd events which happen frequently, panic or an emergency can lead to an increase in congestion which may cause disastrous incidents. Crowd control planning via simulation of people's movement and behavior can promote safe departures from a space, despite threatening circumstances. Up until now, the evolution of distinctive types of crowd behavior towards cooperative flow remains unexplored. Hence, in this paper, we investigate the impact of potential crowd behavior, namely best-response, risk-seeking, risk-averse, and risk-neutral agents in achieving cooperation during evacuation and its connection with evacuation time using a game-theoretic evacuation simulation model. We analyze the crowd evacuation of a rectangular room with either a single-door or multiple exits in a continuous space. Simulation results show that mutual cooperation during evacuation can be realized when the agents' population is dominated by risk-averse agents. The results also demonstrate that the risk-seeking agents tend toward aggressiveness by opting for a defector strategy regardless of the local crowd densities, while other crowd behavior shows cooperation under high local crowd density.

Keywords

Evacuation simulation, cooperation dilemma, evolutionary game theory, agent-based model, behavioral model

1. Introduction

It is expected that 55% of the population of the world living in urban areas today will increase to 68% by 2050.[1] This urbanization will unite people or crowd together in many occasions. Indeed, there are numerous positive effects when people assemble socially, and this demonstrates the fascinating constructive power in a well-organized structure.[2] On the contrary, there are also a few negative aftereffects should the density of people become too high. Examples are sudden evacuation, increased crime, serious traffic setback, and pollution. Moreover, densely occupied areas might also lead to stampedes in circumstances where people are trying to move forcefully away from the congested area because of the crowd's proximity and constant interaction.

Studies have been done to model secure and effective evacuation of mass gatherings such as the Hajj pilgrimage as proposed by Owaidah et al.,[3] where two Hajj rituals, Tawaf and Sayee, are simulated jointly using discrete evacuation simulation, and large festivals as by Ronchi et al.,[4] where evacuation modeling of large-scale music festival using Pathfinder is presented. This includes everyday pedestrian public sites such as shopping complexes and underground subways. Evacuations can be planned, but emergency situations which may cause calamities can arise either due to crowd dynamics or external factors such as incidents of violence, collapse of buildings, tsunamis,[5,6] and unexpected fire accidents. It is reported by Keith and Still[7] that the total number of deaths due to several crowd disaster incidents that happened around the world from

[1]Department of Mechatronics Engineering, International Islamic University Malaysia, Malaysia
[2]School of Computing and Informatics, Universiti Teknologi Brunei, Brunei Darussalam
[3]Division of Natural Sciences, University of Kent, UK

Corresponding author:
Azhar Mohd Ibrahim, Department of Mechatronics Engineering, International Islamic University Malaysia, Jalan Gombak, 53100 Kuala Lumpur, Malaysia.
Email: azhar_ibrahim@iium.edu.my

2010 to 2018 amounted to more than 1700 persons and those crowd disasters occurred mainly due to crowd stampedes where a panicked crowd rushes away to escape from the threat. For instance, Table 1 shows several crowd disasters that occurred during the Hajj season, mainly due to the crowd stampeding.

The simulation of evacuation requires the capability to model individual decisions and behaviour[10] throughout the escape process such as during a stampede,[11] which is strongly affected by the surroundings[12] such as fires,[13–15] smoke conditions,[16] and earthquakes[17,18]. The understanding of human behaviors can minimize the chances of crowd calamities[19] and lead to an effective evacuation. It is evident that the behavior of a crowd is deep-seated and could be altered by external aspects such as clogging, narrow paths, counter flow, and congestion. Nonetheless, accurate modeling and simulation of the crowd behavior might produce an optimum evacuation time and a more secure progression. Besides that, it is important to analyze the behavior of the crowd to maintain safe and improved evacuation flow during congregations. Thus, the overarching aim of this paper is to depict how certain evolutionary optimized crowd behavior can lead to the cooperation that could ultimately enhance the overall evacuation process and quicken the required evacuation time.

This article is organized as follows. Section 2 presents related work that addresses research gaps pertaining to potential evolutionary crowd behavior during the evacuation process. Section 3 describes the agent's cost function, crowd strategies, and crowd behavior associated in a game-theoretic evacuation model, while, section 4 presents the evacuation simulations setup. Next, section 5 discusses the impact of crowd behavior under different conflict costs on the evolution of crowd strategies, cooperative flow and evacuation time. Finally, the potential findings of this research are highlighted in the conclusion section.

2. Related works

Microscopic method is one of the best choices for modeling and examining crowd behavior as the behavior and mobility of the entire population of the area would be affected by the behavior of each agent. Cellular automata (CA),[20] lattice gas,[21] social force,[22] and game theory-[23] based evacuation simulation models are illustrations of microscopic models that are computationally efficient and able to support large parameter spaces for simulation. The general drawbacks are that models are not fully realistic because these models are in discrete space and most of them simulate the crowd movement via probability theory. Furthermore, these models generally assume that all agents have the same size. This seems to be unpractical since in real-world evacuation scenarios, generally evacuating agents are in different sizes. Meanwhile, the social force simulation model is for simulation in continuous space, and it is also able to model the size of each agent. A few examples of the social force model to study the evacuation process are for example the model by Chen et al.[24] where the authors studied the impact of intersecting angles during evacuation using a social force model,[25] presented a mechanism using a social force model to study agents' responses during building evacuation caused by seismic event, while[26] presented the impact of information transmission during evacuation process using a social force model. Even though social force can be used to study different aspects of evacuation process and modeling agents' behavior, the underlying presumption that all of the agents have the same properties might be improbable[27] since a crowd is commonly composed of diverse types of individuals.[28] These limitations can be addressed by hybridizing the social force and game-theoretic models.

In addition, to be able to imitate evacuation scenarios accurately, choices, and preferences of individual types of agents must be contemplated, as the consequences of the unpredictable nature of dynamic behavior of the crowd might lead to hazardous situations. Choices made by involved players (agents) are evaluated by the mathematical models which are modeled using game theory approach.[29,30] Game theory could be employed for appraising the results of the dynamic behavior of the whole crowd. This is because, game-theoretic evacuation simulation enables agents to consider all possible options

Table 1. Crowd disaster during Hajj.[8,9]

Date	Place	Deaths	Reason
2/7/1990	Pedestrian tunnel	1426	Overcrowded
23/5/1994	Al-Jamarat	270	Stampede
15/4/1997	Tent city at Mina	340	Overcrowded
9/4/1998	Jamarat Bridge	>118	Stampede
5/3/2001	Jamarat Bridge	35	Stampede
11/2/2003	Mina	14	Stampede
1/2/2004	Jamarat Bridge	251	Stampede
1/1/2006	Jamarat Bridge	346	Stampede
24/9/2015	Mina	769	Stampede

before selecting the best strategy which suits their own principles. In order to analyze the crowd dynamics entailed in microscopic models, the game-theoretic evacuation model is evidently proven to be impactful.[31,32] Accordingly, in recent years, a large number of researches have suggested to model crowd behavior during evacuation process using game theory.[33] Related research of evacuation modeling and simulation which implements different aspects of game theory such as a spatial game in describing risky agents is proposed by Pärnänen,[10] game theory cost function modeled using distance to the exit and number of agents is proposed by Tian et al.,[33] game theory for room evacuation via lattice gas scheme can be found in Bouzat and Kuperman's study,[34] game theory via a CA environment to study patient and impatient agents are presented by Heliövaara et al.,[35] von Schantz and Ehtamo,[36] while game theory to study the effect of obstacle removal during evacuation is presented by Lin and Wong.[37]

In modeling and simulating evacuation scenarios, it is essential to take account of the crowd's behavior and diverse emergency scenarios as pointed out by Wirz et al.[38] Examples of several recent research works on diverse emergency evacuation scenarios are featured such as in metro station,[13] terminal apron,[39] training school,[40] and also during dense crowd.[41] Xie et al.[13] proposed a stabilized coupled model of agent behavior and computational fluid dynamics model for effectiveness investigation of the fire evacuation in a metro station. The results indicated that the interaction between fire and humans has direct impact on the evacuation based on the fire location and the density. Meanwhile, Guolei et al.[39] developed a model-based fuzzy multiple attribute decision-making framework for evaluation of the passenger service quality and recognizing an optimal layout of the terminal apron. The proposed work was effective in solving the rezoning of the Roll-on/Roll-off/*Passenger* (Ro-Pax) terminal apron and the results showed that rational traffic organization and refined arrangement in the terminal apron can reduce the traffic hazards effectively. Xie et al.[40] developed a fine grid cellular CA model to describe the pedestrian behaviors specifically adult–child behaviors and movement in the corridor during after-class periods at training schools. Hesham and Wainer[41] proposed a model based on centroidal particle dynamics considering the pedestrians' close-range interactions in dense crowds. This method reproduced several phenomena at the microscopic level of emergent crowd evacuation. Although there is plenty of research on crowd behaviors during emergency scenarios, the study on evolutionary optimized behaviors among crowds during the evacuation process, and their efficiency, is yet to be explored deeply.

During a typical evacuation scenario, evacuees tend to cooperate with or defect from other evacuees in order to move toward the preferred path. The evacuees' behavior and their preferred speed tends to affect the evacuation process, generating bottlenecks. Cooperative flow during evacuation is believed to quicken the egress time[34–36] while the higher the number of defectors (aggressive or hawkish agents) in the crowd, the slower the time taken for egress. This condition is also known as the faster-is-slower effect which is the result of higher numbers of conflicts when more defectors move straight for the exit. This produces a clogging condition near the exit[42,43] which delays the time for people to be entirely away from the scene. Therefore, faster time of evacuation is achieved once cooperation among the agents is accomplished. Up until now, the relation of certain potential crowd behavior and its evolution toward cooperative flow has remained little studied. Thus, in this paper, we aim to explore the impact of evolution of potential crowd behavior in achieving cooperation during evacuation and faster evacuation times. Studying the impact on these potential behaviors in an emergency will enhance the evacuees' decision-making abilities during on-site emergency evacuation. The main contribution of this paper is simulation of evacuation scenarios using a game-theoretic approach by incorporating evolution of certain potential crowd behaviors, viz. risk-seeking, risk-averse, risk-neutral, and best-response, with their potential strategies, namely cooperator, defector, evaluator, and retaliator and how their evolution during the evacuation process can lead to cooperative flow and hence achieve fast evacuation.

3. Model definition

In this work, the evacuation process in a single-door rectangular room of size $L \times W$ with a door length of 1 m is analyzed. We consider a continuous space and continuous time where the agents' movement toward the exit is modeled by the social force model.[44] The social force model governs the movement of the agents through social forces which are a measure of the internal motivations for the agents to move in a certain direction. Here, we utilized the social force model as proposed by Helbing and Molnár.[45] Then, how agents choose their strategies and its consequences to the evacuation process is modeled based on game theory approach. Details of the combined social force model and game-theoretic approach in updating agents' strategies are sketched in Figure 1. As depicted in the flowchart in Figure 1, when the interaction or conflicts among evacuees occur, which is normally during bottlenecks, clogging, narrow path, or congestion, how the evacuees view the significance of the evacuation scenario and the utility they will receive on updating their strategies is known as the agent's cost function, and it is modeled using game theory.

In most of the literature pertaining to an agent's cost function using a game-theoretic approach, the cost

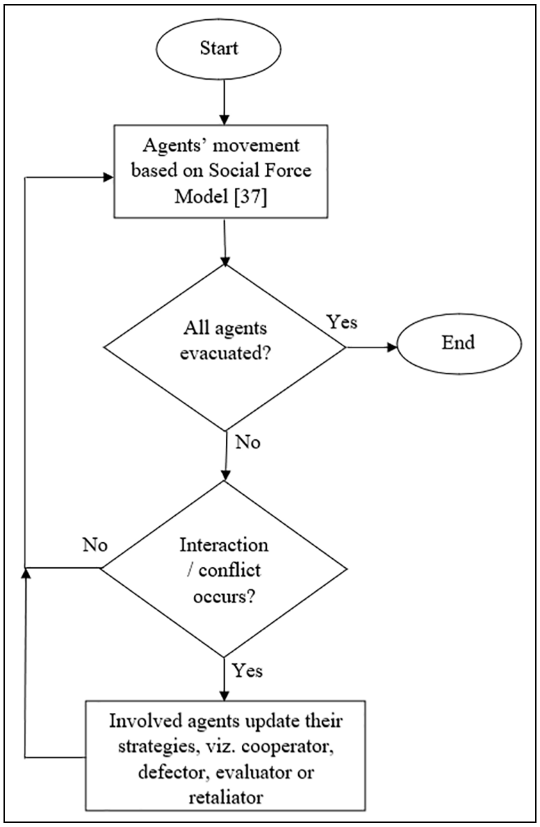

Figure 1. The proposed process flow of the integration of a social force model and a game-theoretic approach in updating agents' strategies.

Table 2. Payoff table as by Zheng and Cheng;[31] "polite" indicating agent will remain still by allowing others to exit, "normal" referring to agent escape in order, while "vying" indicating agent is competing to move.

Player 1/player 2	Polite	Normal	Vying
Polite	0, 0	0, *b*	0, *b*
Normal	*b*, 0	*b*/2, *b*/2	0, *b*
Vying	*b*, 0	*b*, 0	$-c$, $-c$

Table 3. Payoff table as by Shi and Wang.[30]

Player 1/player 2	*C*	*D*
C	*b*–*c*/2	*b*–*c*
D	*b*	0

Table 4. Payoff table as by Heliövaara et al.,[35] von Schantz and Ehtamo.[36]

Player 1/player 2	Impatient	Patient
Impatient	$\frac{T_0}{T_{ij} - T_{ASET} + T_0}$	-1
Patient	1	0

function that describes the evacuation game is assumed to be constant. In Shi and Wang's[30] and Zheng and Cheng's[31] studies, the cost functions are assumed to be constant values as described in Tables 2 and 3, respectively. For the cost function in Table 3, the result accounts only for the row-agent and for others with identical interaction. Here in Shi and Wang's study,[30] *b* refers to perfect benefit of the game, while *c* refers to labor cost in the game. Shi and Wang[30] introduced a new parameter $r = c/(2b - c)$ and the effect of the agents' cost function toward evacuation is tested by altering values of the parameter *r*. Meanwhile in Heliövaara et al.'s[35] and von Schantz and Ehtamo's studies,[36] the cost function depends only on the estimated evacuation time (T_{ij}), since T_o (time needed for agents before beginning to play the game) and T_{ASET} (available safe egress time) are set to be constant values as shown in Table 4. In Table 4, the results account only for the row-agent and for others with identical interaction. Parameters T_o refers to the time needed for agents before beginning to play the game, T_{ij} refers to the estimated evacuation time, while T_{ASET} refers to the available safe egress time. Here, the authors neglect the conflict cost and conflicting neighboring agents in determining the agents' cost function where in reality, the agents' cost function depends also on these parameters. Meanwhile, in Bouzat and Kuperman's study,[34] conflicting neighboring agents are included as shown in Table 5. In this table, *C* refers to cooperator(s), *D* refers to defector(s), *P* is a punishment to the defectors, *n* refers to the total number of competing agents, while *m* refers to the number of cooperators in the competing agents. In this work, the authors have neglected the importance of dynamic changes of escape time during evacuation scenarios. The aforementioned problems were solved by Ibrahim et al.;[46] however, Ibrahim et al.[46] focused only on the behavior of crowds that can lead to crowd disaster, while this research aims to investigate how evolution of certain crowd behavior could lead to cooperative flow which will lead to fast and safe evacuation.

Details of the evacuation simulation model using a game-theoretic approach are as follows. Here, the egress operation is perceived as an evacuation game played with the aim to decrease the egress time. The estimated time of evacuation (T_i) for each agent is defined as

$$T_i = \frac{d_i}{\|v(\boldsymbol{r}, t)\|}$$

where d_i is the distance of an agent to the exit and $\|v(\boldsymbol{r}, t)\| = \sum_j v_j/n$ is an agent's local speed in which v_j

Table 5. Payoff table as by Bouzat and Kuperman.[34]

Player 1/competing agents	$(n-1)C$, $0D$	mC, $(n-1\ m)D$
C	$1/n$	0
D	$1/P$	$\frac{1}{(n-m)(n-m-1)P}$

is the agent's speed at (t), and n is the number of agents within distance less than 80 cm around the center location (r) of ith agent at time (t).

In circumstances where more than a single agent tries to move in a similar direction at the same time, conflict is bound to happen. Only one agent will be able to move whenever a conflict occurs. Interaction among agents with their nearest neighbors occurs in each time step. The neighboring agents as suggested by Mohd Ibrahim et al.[47] are considered here as conflicting agents where the winners of the conflicts and also the agents who are uninvolved in conflicts with their neighboring agents are able to move.

The winner can outdistance other agents and reduce his or her approximated evacuation time by Δt. By doing so, the winner can reach to the preferred position and gain the utility. At the same time, the loser(s) approximated time of evacuation will increase by the same number Δt and they will linger at the existing location losing the utility. This will result the reduction of the cost of each winner agent to a utility which will be $\Delta u(T_{i(i_c)})$ and for the loser(s) agent the cost will identically increase. The simulation halts once all the agents have evacuated.

The distance d_i between the agent and the exit eventually gets decreased by d which is described as $\Delta d = \|v(\boldsymbol{r}, t)\| \times \Delta t$, for each step taken by the agent. Here, $\|v(\boldsymbol{r}, t)\|$ is the mean speed of the agents around the central position $\boldsymbol{r}$ of the ith agent at time t. Moreover, Δt is assumed to be a constant value of 0.8 s as proposed by Mohd Ibrahim et al.[47] The estimated evacuation time of conflicting agents for each step is $\Delta u(T_{i(i_c)}) = \Delta d/v_i$, where v_i refers to the agent's desired speed. Whenever there is a vacant space, the winning agent will choose this as the desired speed to move there.[46]

Here, an n agents $\times$ 4 strategies symmetric egress game is considered where the strategies are cooperator (C), defector (D), evaluator (E), and retaliator (R). Cooperator will never fight for the intended position. In contrast, defector will be impatient in moving to a preferred spot. Evaluator will appraise the opponent in terms of size. If

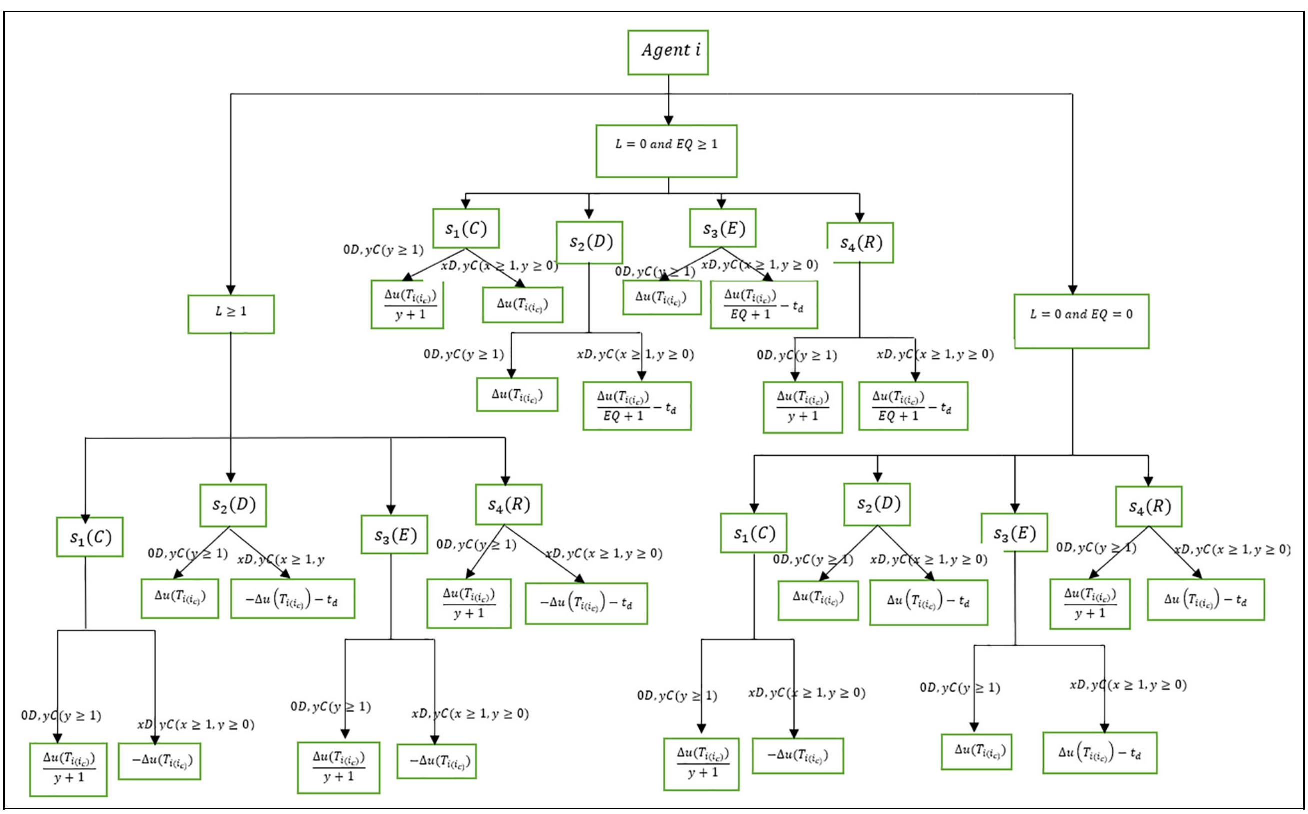

Figure 2. $n \times 4$ evacuation game theory tree diagram (L: number of large defector opponent(s) to current agent i, EQ: number of equal defector opponent(s) to current agent i, x: number of neighboring defector(s) to current agent i, y: number of neighboring cooperator(s) to current agent i, s_m refers to strategy of current agent i as indicated in the bracket.

the opponent is huge in size, the evaluator will act as a cooperator, whereas if the opponent is at most equal in size, it will act as a defector, while retaliator defects only when the adversary acts as defector. In general, when two retaliators meet, both will act as cooperators. When there is conflict among defectors and cooperators, the defectors will try and push to move. When the defectors try and push among themselves in order to move, inevitably it will result in a little time delay t_d which is considered as conflict cost. Details of the $n \times 4$ evacuation game[46] are sketched in the game theory tree diagram in Figure 2 and summarized as in below.

The $n \times 4$ evacuation game is based on different numbers of defectors and cooperators, and there will be three cases. In the first case, the number of defectors (n_{def}) is greater than one and the number of cooperators (n_{coop}) is greater than or equal to zero. This case has three distinct sub-cases. In the first sub-case, the number of large defectors is one so, he or she will be able to move while the rest of the defector(s) and all the cooperators will remain at the same location. Payoff for the large defector, defectors, and cooperators are respectively: $\Delta u(T_{i(i_c)}) - t_d$, $-\Delta u(T_{i(i_c)}) - t_d$, and $-\Delta u(T_{i(i_c)})$. In the second sub-case, the number of large defectors is greater than 1 so, one of the large defectors will be able to move while the rest of the defector(s) and all the cooperators will remain at the same location. Payoff for the large defector ($L_{n_{def}}$-number of large defector(s)), defectors, and cooperators are respectively: $(\Delta u(T_{i(i_c)})/L_{n_{def}}) - t_d$, $-\Delta u(T_{i(i_c)}) - t_d$, and $-\Delta u(T_{i(i_c)})$. In the final sub-case, the number of large defectors is 0, so one of the defectors will be able to move while the rest of the defector(s) and all the cooperators will remain at the same location. Payoff for the defectors and cooperators are respectively: $((\Delta u(T_{i(i_c)}))/n_{def}) - t_d$ and $-\Delta u(T_{i(i_c)})$. In the second case, the number of defectors is one and the number of cooperators is greater than or equal to 1. So, the single defector will be able to move while all the cooperators will remain at the same location. Payoff for the defectors and cooperators are respectively: $\Delta u(T_{i(i_c)})$ and $-\Delta u(T_{i(i_c)})$. In the final case, the number of defectors is zero, and the number of cooperators is greater than 1. So, there is no winner and loser, the payoff is set as if all were cooperators, as the conflicting agents will move together with the crowd based on the social force model, and the payoff for the cooperators is $(\Delta u(T_{i(i_c)}))/n_{coop}$.

Besides that, four types of agent behavior viz., risk-seeking, risk-averse, risk-neutral, and best-response[46,47] are examined. Different types of agents have the same cost function but may have different preferences or strategies. These different strategies of the agents are owing to the different risk attitude of the agent types. The details of these behaviors as follows:

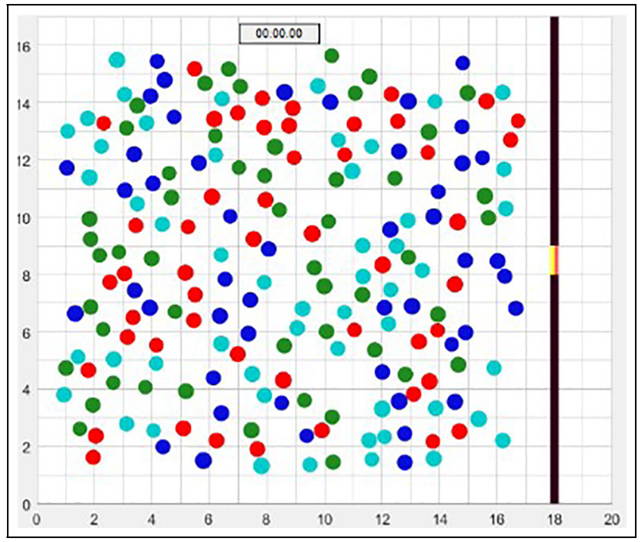

Figure 3. Evacuation simulation at the beginning with 200 agents at random positions (red: defector, green: cooperator, blue: evaluator, and cyan: retaliator).

- Risk-seeking or risk-loving can be recognized as the particular approach of agents where they try to achieve maximum utility under ambiguous scenarios anticipating quick evacuation. It is a maximax approach in game theory.
- Risk-averse stands for the behavior of the agents in circumstances in which they look for the best out of the worst results. It is a maximin approach in game theory.
- Risk-neutral behavior refers to agents who prefer to opt for conservative selection during unpredictable scenarios where only a very small amount of information is known about the inclination of other opponents. It is a minimax regret approach in game theory.
- Best-response behavior indicates the capability of agents to react by observing other agents' strategies in their surrounding during previous instances.

An agent will choose either to be cooperator, defector, evaluator, or retaliator based on his or her behavior. In each simulation, an agents' behavior is fixed, while the other three behaviors were randomly selected. For example, if the number of risk-seeking agents is fixed at 20 agents, the remaining 180 agents will be chosen randomly from the remaining possible behaviors.

4. Simulation

We simulate different features of human escape behavior in crowded environments with a single exit, including, but

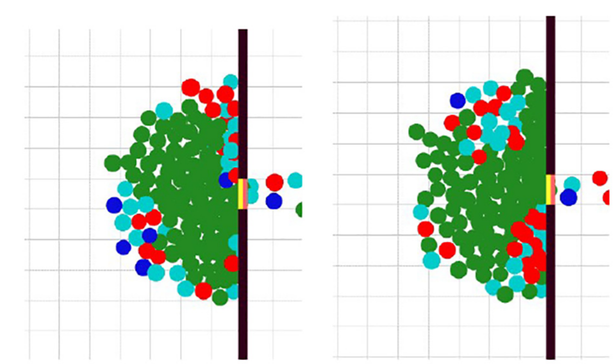

Figure 4. Examples of equilibrium configuration for all best-response agents (red: defector, green: cooperator, blue: evaluator, cyan: retaliator): (a) t_d = 0.5 s and (b) t_d = 1.2 s.

not limited to, discotheques, stadia, lecture halls or rooms in general and other event areas. The scope of this section is set to examine the crowd escape behavior in environments with a single exit because the critical conditions during emergency scenarios may arise due to the crowding and movement at vulnerable locations such as at exit doors, gates, and passages.[48] Bottleneck frequently occurs at the point when hindrances cause disturbances or when the space limits the flow. Critical conditions for the crowd could happen when a densely packed crowd moves through the bottleneck. This is because of the high pressure that spreads among the crowd. Furthermore, agents also could fall due to the forces that spread among the crowd.[48] We choose a room size for the evaluations. The results do not depend on the room size, as long as there are enough agents of different types in the room. For the simulations, the evacuation process in a single-door rectangular room of size 18 m $\times$ 17 m with a door length 1 m is as shown in Figure 3 with initial 200 agents that are randomly located.

Simulations are performed in accordance with a heterogeneous population where risk-seeking, risk-averse, risk-neutral, and best-response agents are merged together to enable us to examine the effect against egress aspects. For improved comprehension of crowd dynamics and the time of egress, the average strategies achieved by the crowd during equilibrium state are examined for different time delays as a result of conflicts, by repeating the simulations with different random frequencies of cooperators, defectors, evaluators, and retaliators placed at random initial locations for 10 runs.

The average values are examined for the time frame of 15s to 70% of total evacuation time since, during these intervals, the crowd is in equilibrium state where they form an arch-like blocking near the exit as shown in Figure 4. For each simulation type, the type of one of the agents' behavior is fixed while the other three behaviors are selected at random.

5. Results and discussion

First, the effect of different proportions of specific crowd behavior toward mean crowd strategies is investigated for different conflict time delays t_d as displayed in Figures 5 and 6. First, for best-response agents, when t_d is 0.5 s, it is observed that preferred strategies for agents in the crowd are to become evaluator and defector as shown in Figure 5(a). Although percentages of retaliator and cooperator strategy increase twofold when the proportion of the best-response agents is increased from 0% to 100%, it is still less compared to the percentages of evaluators and defectors. In contrast, when t_d is increased to 1.2 s, the result is totally different from the previous case where the cooperator strategy has become the preferred strategy which is about two-thirds of possible crowd strategies no matter what are the different proportions of best-response agents. The retaliator strategy has become the least preferred strategy where its percentage is about 1%–3% only as shown in Figure 6(a).

For risk-averse agents, when t_d is 0.5 s, the result is quite similar to the best-response agents' result in Figure 5(a) except that the percentage of retaliator strategy has increased to threefold when the proportion of risk-averse agents increased from 0% to 100% as shown in Figure 5(b). However, when t_d is increased to 1.2 s, the cooperator strategy has become dominant and it is approaching full mutual cooperation when the proportion of risk-averse agents is 100% as displayed in Figure 6(b). For risk-neutral agents, when t_d is 0.5 s (Figure 5(c)), it is observed that the percentages of evaluator and defector strategy increase and the percentages of retaliator and cooperator strategy decrease whenever the proportion of risk-neutral agents is increased. In contrast, when t_d is increased to 1.2 s (Figure 6(c)), the cooperator strategy has become the dominant strategy similar to the risk-averse agents' result in Figure 6(b). Then, for risk-seeking agents (Figure 5(d)), when t_d is 0.5 s, the result is quite similar to the risk-neutral agents' result in Figure 5(c). When t_d is increased to 1.2 s, unlike other strategies, the cooperator strategy decreases in frequency, while evaluator and defector strategies increase whenever the proportion of risk-seeking agents is increased, as shown in Figure 6(d).

Typical results pertaining to the evolution of these strategies, viz. cooperator, defector, evaluator, and retaliator are shown in Figures 7–10. High local crowd density will lead to increase in crowd forces,[49] thus will increase the time delay t_d, while low local crowd density will require less time delay t_d. Therefore, we assume that t_d = 1.2 s corresponds to high local crowd density while t_d = 0.5 s

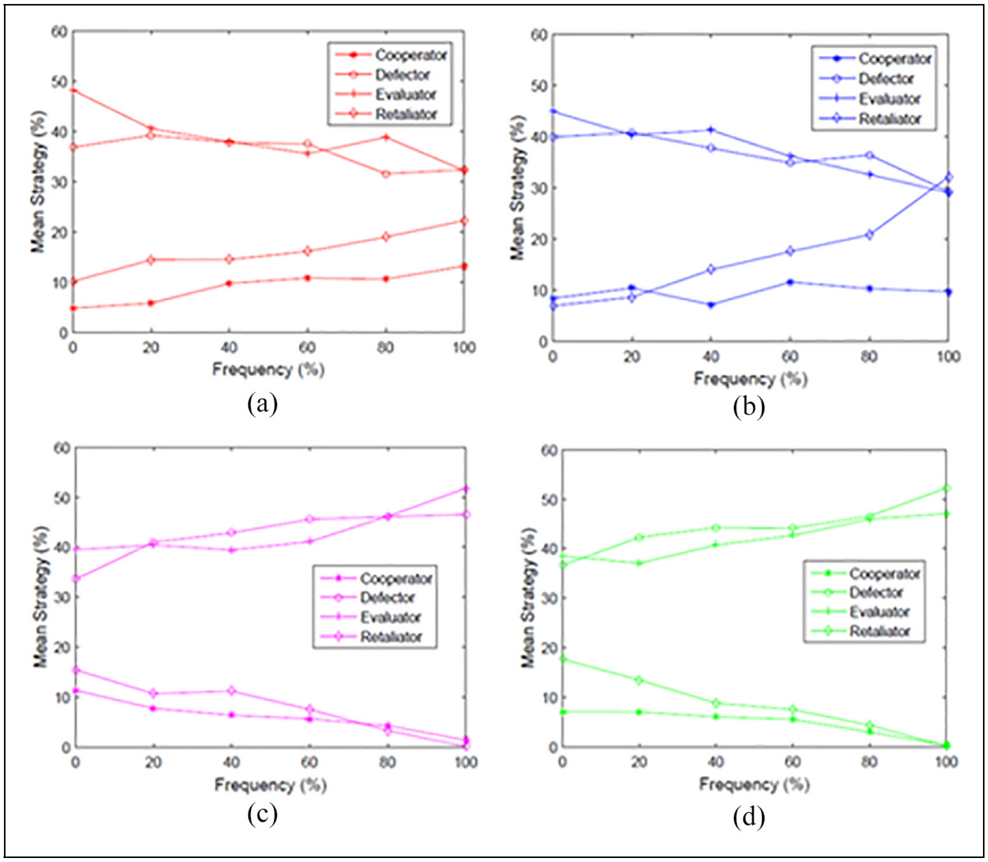

Figure 5. Achieved mean crowd strategy percentages for different proportions of fixed crowd behavior. For instance, subfigure (a) shows the effect of different proportions of best-response agents toward mean crowd strategies. Parameter used: t_d = 0.5 s: (a) best-response agents, (b) risk-averse agents, (c) risk-neutral agents, and (d) risk-seeking agents.

corresponds to low crowd density. As observed from these results, both in low- and high-density cases, about half of the best-response agents prefer to be cooperators, while another half prefers to be evaluators and defectors (Figure 7). For risk-averse and risk-neutral agents, in the high-density case, about all of them prefer the cooperate strategy. However, risk-averse agents evolve quite fast to become a cooperator compared to risk-neutral agents (Figures 8(b) and 9(b)).

In the low-density case, half of the risk-averse agents prefer to be cooperators, while most of the risk-neutral agents prefer to be evaluators and defectors (Figures 8(a) and 9(a)). It also can be observed that risk-seeking agents prefer the defect strategy irrespective of the local crowd densities (Figure 10).

Next, the effect of crowd behavior toward the percentage of *patient* agents during evacuation is examined. Here, patient agents have an overall cooperative strategy which includes cooperator strategy and also cooperator strategy embedded in evaluator and retaliator. This study will assist us in better understanding how mutual cooperation is achieved by crowds during evacuation. Figure 7(a) indicates that when the conflict time delay t_d is quite low at 0.5 s, about less than 15% of the crowd prefers the cooperator strategy. Moreover, mutual defection is nearly achieved when the distribution of the risk-seeking agents and risk-neutral agents are 100% each.

Conversely, cooperative strategy is increasing when t_d is increased to 1.2 s except in the case of risk-seeking agents (Figure 11(b)). To be more precise, for risk-averse and risk-neutral agents, whenever their proportions are increased, the percentages of cooperative strategy increase as well. Mutual cooperation is nearly achieved in the case of risk-averse agents when their proportion is 100%. For best-response agents, a cooperative strategy is used in more than half of all cases. Meanwhile, percentages of cooperative strategy decrease whenever the proportion of risk-seeking agents is increased. Mutual defection is nearly achieved when the proportion of the risk-seeking agents is 100%. The result in Figure 11 shows that risk-seeking

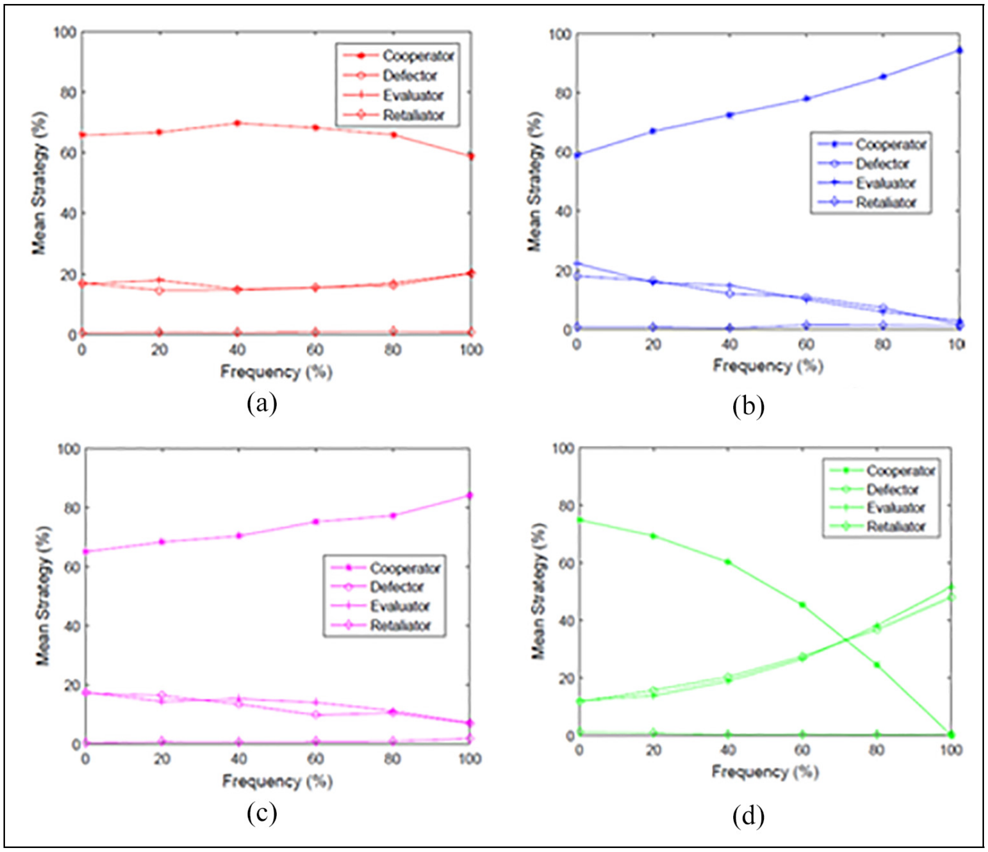

Figure 6. Achieved mean crowd strategy percentages for different proportions of the fixed crowd behavior. For instance, subfigure (a) shows the effect of different proportions of best-response agents toward mean crowd strategies. Parameter used: t_d = 1.2 s: (a) best-response agents, (b) risk-averse agents, (c) risk-neutral agents, and (d) risk-seeking agents.

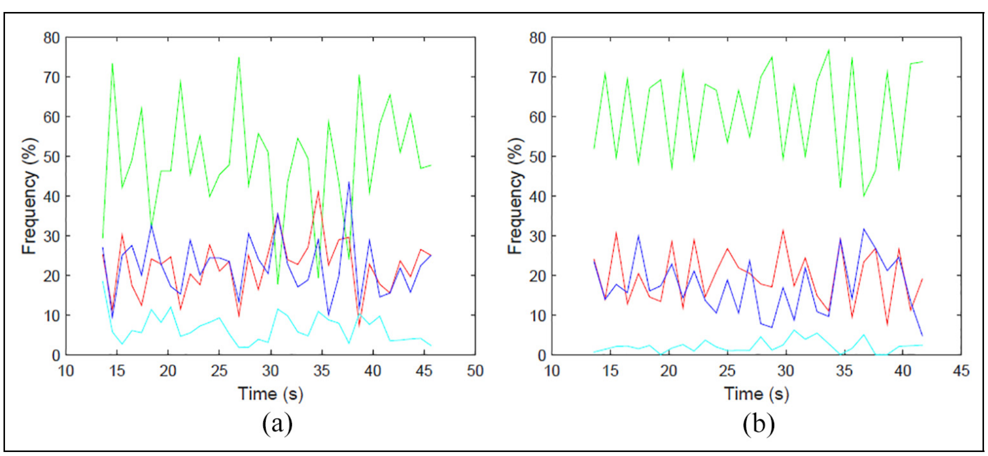

Figure 7. Evolution of strategies of the crowd in an evacuation simulation for all best-response agents (red: defector, blue: evaluator, green: cooperator, cyan: retaliator): (a) t_d = 0.5 s and (b) t_d = 1.2 s.

agents are inclined toward a defector strategy regardless of the amount of conflict time delays, while other crowd behavior shows a cooperative strategy when there is an increase in conflict time.

Next, the effect of crowd behavior on mean escape time is studied. The final result for this simulation is shown in Figure 12. From the simulation result in Figure 12(a),

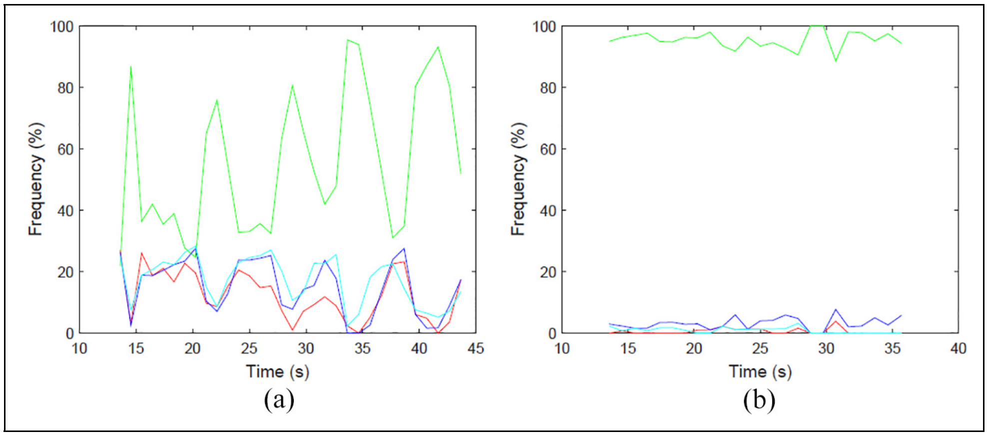

Figure 8. Evolution of strategies of the crowd in an evacuation simulation for with all risk-averse agents (red: defector, blue: evaluator, green: cooperator, cyan: retaliator): (a) t_d = 0.5 s and (b) t_d = 1.2 s.

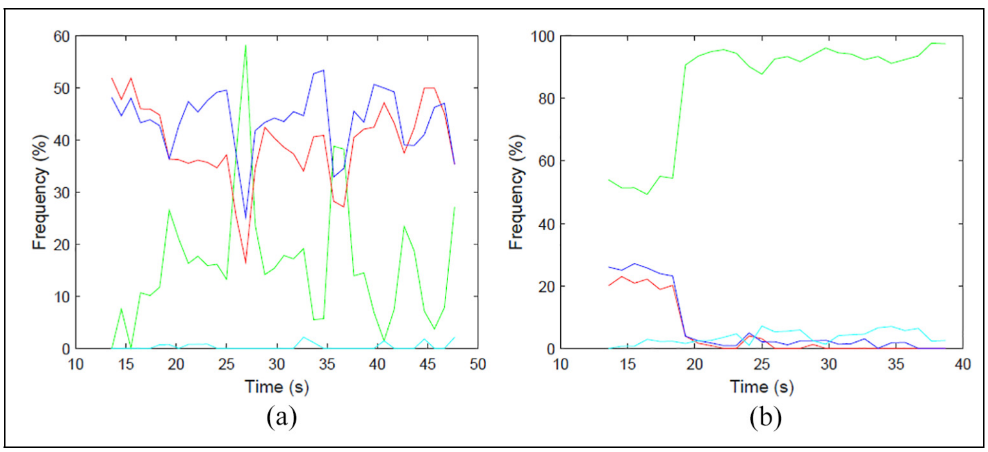

Figure 9. Evolution of strategies of the crowd in an evacuation simulation for all risk-neutral agents (red: defector, blue: evaluator, green: cooperator, cyan: retaliator): (a) t_d = 0.5 s and (b) t_d = 1.2 s.

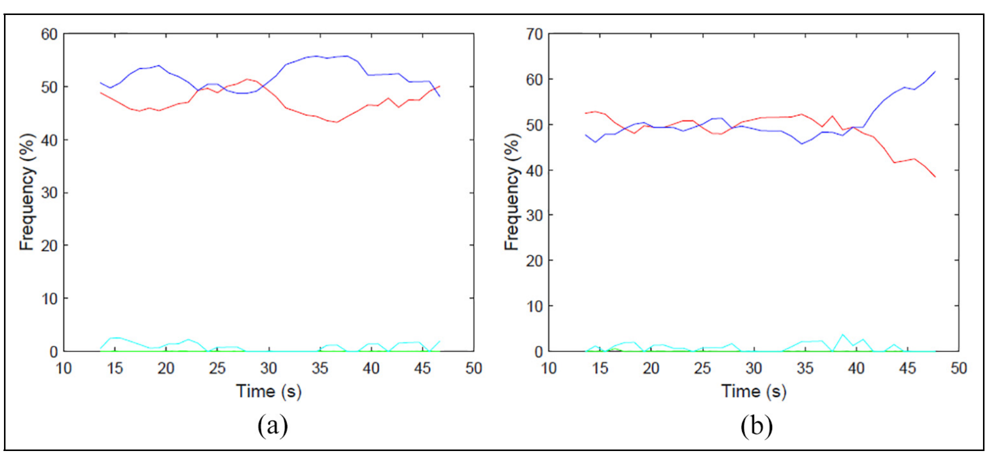

Figure 10. Evolution of strategies of the crowd in an evacuation simulation for all risk-seeking agents (red: defector, blue: evaluator, green: cooperator, cyan: retaliator): (a) t_d = 0.5 s and (b) t_d = 1.2 s.

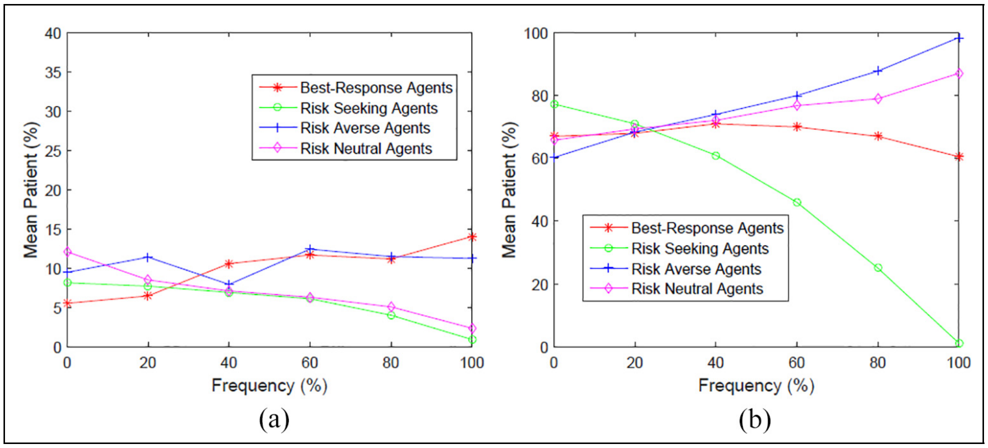

Figure 11. The effect of different proportions of crowd behavior toward the mean of overall patient agents: (a) t_d = 0.5 s and (b) t_d = 1.2 s.

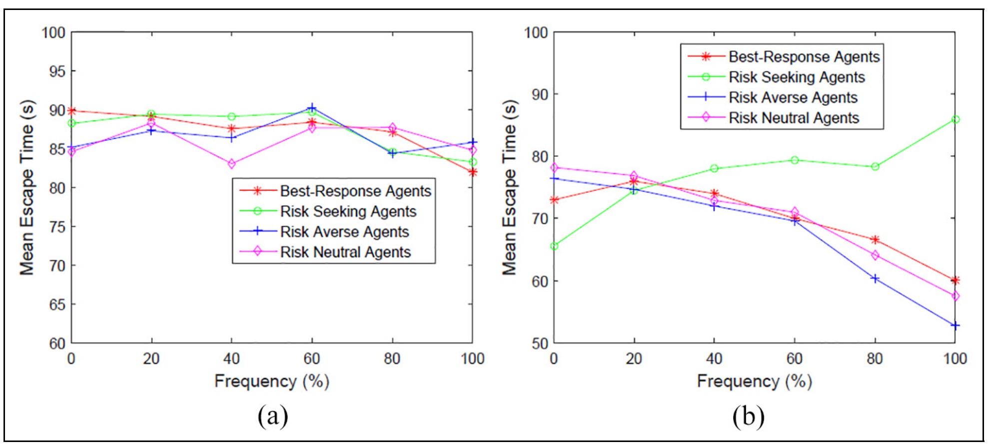

Figure 12. The effect of different proportions of crowd behavior toward mean escape time: (a) t_d = 0.5 s and (b) t_d = 1.2 s.

which is for a conflict time delay of 0.5 s, the average escape time for all types of agents is almost similar where this average escape time is quite high. This is due to the majority of the crowd preferring a defector strategy as shown in Figure 11(a), and this led to a pushy behavior among the crowd. The combined result of Figures 11(a) and 12(a) indicates that the larger the number of impatient agents (which means total defector strategy including defector strategy in evaluator and retaliator strategy as well), the slower the egress time.

This scenario is referred to as the faster-is-slower effect, which happens due to the increased number of conflicts when more defectors tend to move straight toward the exit. This results in a clogging effect near the exit.[46,47] This clogging slows down the total escape time. Figure 12(b) indicates that when t_d is increased to 1.2 s, average escape time tends to be faster whenever the proportion of best-response, risk-averse, and risk-neutral agents is increased. The average escape time tends to be fastest when the risk-averse agents' population increases. In contrast, when the risk-seeking agents' population increases, the average escape time becomes slower and this indicates the faster-is-slower effect even though risk-seeking agents look for gaining maximum utility in order to achieve fast evacuation. In a nutshell, it can be inferred that faster evacuation time occurs once mutual cooperation among agents is achieved, which happens when agents' population is dominated by risk-averse agents.

Finally, as the average escape time is the fastest and mutual cooperation is achieved when the population is full of risk-averse agents, we further simulated multi-exit evacuation scenarios to study the evacuation flow when the population is full of risk-averse agents. Here, exit choice is randomly selected, as this paper mainly focuses on the effect of evolution of behavior in achieving mutual cooperation during the evacuation process. Figure 13 shows some examples of the evacuation scenarios at different time steps. Figure 13(a) is a simulation of the experimental

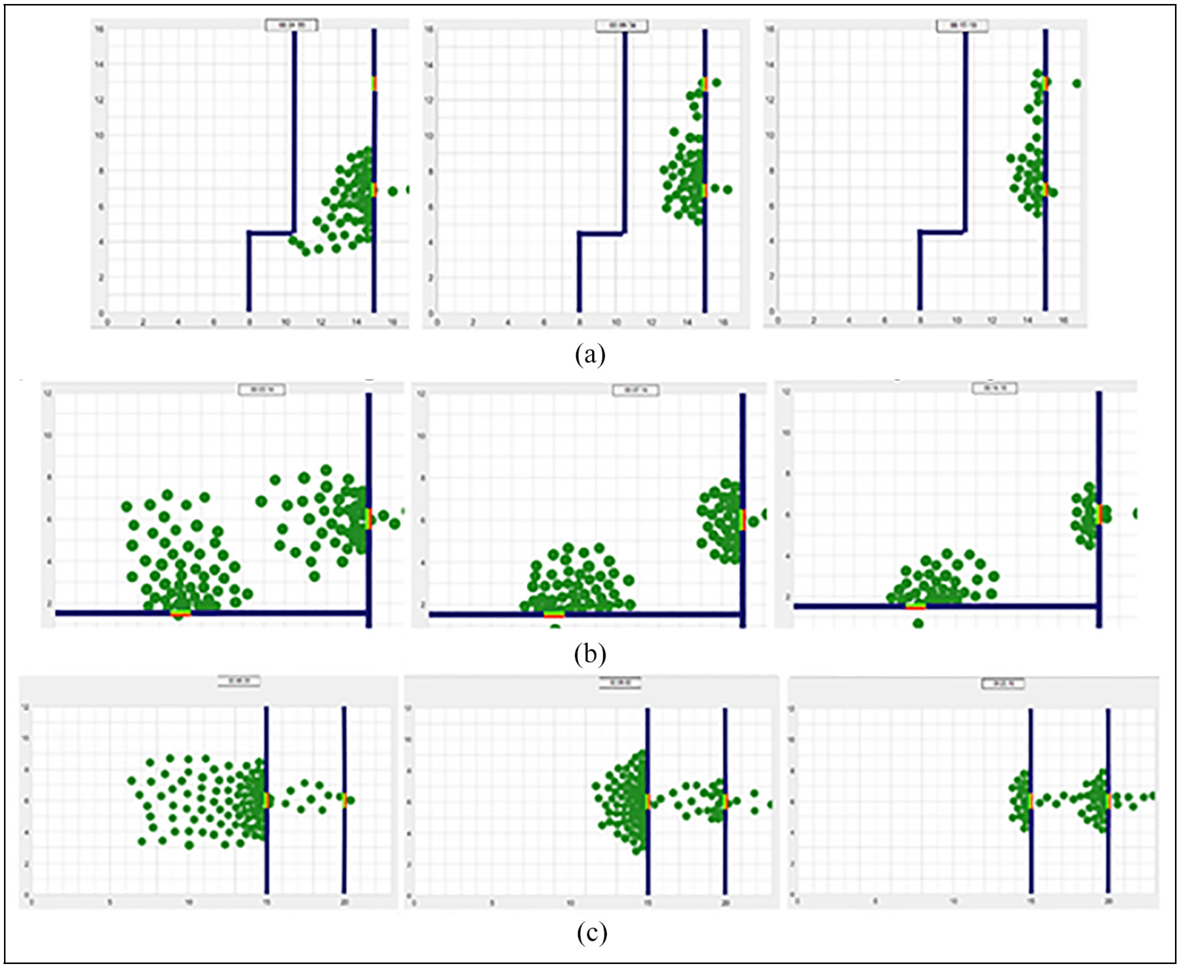

Figure 13. Examples of multi-exit simulations at different time steps: (a) evacuation simulation of 54 agents similar to the experimental evacuation study done by Heliövaara et al.,[50] (b) evacuation simulation of 100 agents, and (c) evacuation simulation of 100 agents in two sequential rooms.

evacuation by Heliövaara et al.[50] that was conducted in a corridor with two exits located asymmetrically. Our multi-exit evacuation simulation in Figure 13(a) is in agreement with the experimental evacuation by Heliövaara et al.[50] where our simulated agents behaved very similar to the participants by Heliövaara et al.[50] in which they move cooperatively by not pushing other agents around them and so they are able to exit the door more efficiently. Figure 13(b) shows multi-exit simulation in a single large room, while Figure 13(c) shows evacuation simulation in two sequential rooms. To conclude, our simulation of multi-exit evacuation scenarios with the crowd population full of risk-averse agents shows smooth evacuation flow as mutual cooperation is favored by all agents. This smooth evacuation flow will lead to minimal evacuation time as shown in Figure 12.

6. Conclusion

This paper aims to depict how the evolution of certain crowd behavior can lead to cooperation during the evacuation process. In order to achieve this aim, we have simulated evacuation scenarios in continuous space using the game-theoretic and social force model and studied the effect of evolution of risk-seeking, risk-averse, risk-neutral, and best-response agents' behavior in achieving mutual cooperation flow and faster evacuation time. The findings of this paper can be summarized as follows:

- For the case of low density which is when the conflict time delay is 0.5 s, this paper found that the preferred strategies for the crowd are to become defectors.

- For the case of high density which is when the conflict time delay is 1.2 s:
  - For risk-averse and risk-neutral agents, whenever their proportions are increased, the proportion of cooperator strategy is increased as well.
  - Mutual cooperation is nearly achieved when agents' population is full of risk-averse agents.
  - The average escape time tends to be fastest when the risk-averse agents' population gets increased.
- Based on the simulation results, the proposed evacuation model is able to confirm the faster-is-slower effect: that the larger the number of impatient agents, the slower the egress time.

We hope that these findings provide insight into important factors that can improve evacuation. There is a relationship between evacuation efficiency and the architectural design of the building, stairs, and floors that should be investigated. In complex buildings, the evacuation efficiency for the simulation of crowd evacuation while considering complex architectural design of the building (e.g. shape, stairs, rooms, floors, and exits) remains a challenge and needs further research. Besides that future work could focus on the refinement of the types of agents, using results from psychology. Our simulations show that game-theoretic approaches could play a significant role toward building sophisticated evacuation models. We have demonstrated the feasibility of the proposed approach for the typical case of a simple one-room model and have shown that it is easy to extend the multi-agent simulations for a given building geometry.

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ORCID iD

Azhar Mohd Ibrahim https://orcid.org/0000-0003-3294-2249

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Author biographies

Azhar Mohd Ibrahim is an assistant professor at International Islamic University Malaysia (IIUM). He has completed his PhD at the School of Computer Sciences, Universiti Sains Malaysia under research theme of crowd dynamics. His research focuses on evacuation models, reinforcement learning, and remote sensing. He has published articles in reputed high-impact journals (Plos One, ACM TIST, Physica A and JASSS), executing several research grants and supervising PhD scholars. He has received several honors including the recipient of the best student award for Master of Science by research, 29th IIUM convocation ceremony and the winner of the 3MT thesis competition held at the Computer Science Postgraduate Colloquium at Universiti Sains Malaysia in 2016.

Ibrahim Venkat is serving as an associate professor at the School of Computing and Informatics, Universiti Teknologi Brunei. He is also a honorary senior research fellow of the University of Kent. His research interests include evacuation models, computer vision, intelligent systems, and bio-inspired computing. He has been contributing interesting articles in reputed journals (IJCV, IEEE, and ACM), organized reputed conferences, executed several research grants, and guided many PhD scholars. He has received numerous honors including the prestigious James-Watt Scholarship, Gold medals from Malaysian Education Ministry and Korea.

Philippe De Wilde is professor of artificial intelligence in the Division of Natural Sciences at the University of Kent, United Kingdom. Between 2014 and 2020, he was deputy vice-chancellor (US: Vice-President) for Research & Innovation at the University of Kent. Between 2007 and 2014, he was Head (US: Dean) of the School of Mathematical and Computer Sciences and a member of the University Executive, Heriot-Watt University, with campuses in Edinburgh, Dubai, and Malaysia. He obtained the PhD degree in mathematical physics and the MSc degree in computer science in 1985 from Ghent University, Belgium. He was lecturer and senior lecturer in the Department of Electrical Engineering, Imperial College London, between 1989 and 2005. He has published 57 journal papers and 56 conference papers. He has published four books, including ''Neural Network Models,'' Springer, 1997, and ''Convergence and Knowledge-processing in Multi-agent Systems,'' Springer, 2009. He started contributing to multi-layer feed-forward neural networks in 1987. His work with British Telecom from 1994 to1999 has contributed to scalable mobile apps. He is a fellow of the British Computer Society, a fellow of the Institute of Mathematics and its Applications, and a senior member of IEEE.

Muhammad Rabani Mohd Romlay received B. Eng (Hons) and MSc degree in Mechatronics Engineering from International Islamic University Malaysia (IIUM) & currently pursuing PhD from the same instituition. The focus of his previous works includes neural network, data science, machine learning, rainfall-runoff, autonomous vehicle, and navigation aids for the visually impaired people. Actively participating in conferences and exhibitions, he has received numerous awards which include medallist in the IRIE 2014 and ORKID WEC 2017 and participation in KERICE 2019 and KERICE 2020. His current research area covers the field of machine-learning, machine vision, artificial intelligent, autonomous robot, object recognition and identification, and feature extraction.

Alala Bahamid is pursuing PhD at the International Islamic University Malaysia (IIUM). His current research is in crowd evacuation, multi-agent systems, reinforcement, and machine-learning. He received B. Eng. (Hons) and MSc degree in Mechatronics Engineering at IIUM.