Uncertainty in spatial evacuation model

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Abstract

Pedestrian movements in crowd motion can be perceived in terms of agents who basically exhibit patient or impatient behavior. We model crowd motion subject to exit congestion under uncertainty conditions in a continuous space and compare the proposed model via simulations with the classical social force model. During a typical emergency evacuation scenario, agents might not be able to perceive with certainty the strategies of opponents (other agents) owing to the dynamic changes entailed by the neighborhood of opponents. In such uncertain scenarios, agents will try to update their strategy based on their own rules or their intrinsic behavior. We study risk seeking, risk averse and risk neutral behaviors of such agents via certain game theory notions. We found that risk averse agents tend to achieve faster evacuation time whenever the time delay in conflicts appears to be longer. The results of our simulations also comply with previous work and conform to the fact that evacuation time of agents becomes shorter once mutual cooperation among agents is achieved. Although the impatient strategy appears to be the rational strategy that might lead to faster evacuation times, our study scientifically shows that the more the agents are impatient, the slower is the egress time.

Keywords: Spatial evacuation, crowd behaviors, uncertainty, game theory

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1. Introduction

Crowd dynamics have important applications in evacuation management systems relevant to organizing safer large scale gatherings including pilgrimages. No doubt, there are many positive effects of bringing people together. However, there are also several negative outcomes when the density of people grows too high, such as overcrowding and crowd stampedes which occur due to the proximity of people and their frequent interactions.

Dedicated research is ongoing in several fields, including the area of crowd dynamics, to propose various effective planning strategies to avoid crowding disaster. Research on crowd dynamics from both theoretical [1, 2, 3, 4, 5] and experimental perspectives [6, 7, 8, 9] involves multi-disciplinary combinations of physics, computer vision, optimization, computational mathematics, psychology, sociology, strategic management and so on. Physics has been inspiring the development of pedestrian dynamic models. Pedestrian dynamic models can be classified into different types depending upon how the scheme treats the pedestrians and the level of detail of the models as follows:

(1) Microscopic models [2, 10, 11, 12, 13, 14], which consider individual pedestrian behavior separately as a particle. The pedestrian behavior in these models is often described by their interactions with other pedestrians in the system.
(2) Macroscopic models [15, 16, 17], which neither make distinctions between individual pedestrians nor describe their individual behavior but consider the pedestrian flow in terms of density, average velocity and flow patterns.
(3) Mesoscopic models [18, 19], which model a small group of people in the same environment where every group has its own identical behavior. Mesoscopic models also combine the properties of the macroscopic and microscopic by considering a crowd as a whole and at the same time consider individual internal forces as well.

Modeling and simulation of crowd evacuation, which has been an active research topic amidst a diverse range of research communities, can be broadly classified into three categories [20] as follows:

(1) Individual pedestrians: Each of the evacuees have a certain preference to follow when they are subject to an evacuation scenario. As such, each evacuee will try to maximize their own utility.
(2) Interaction among individuals: This could also contribute to the smoothness of the evacuation process. During emergency evacuation, usually some sort of interaction happens among evacuees. Some of the evacuees would tend to follow the majority, while others would rush towards the direction of exits which could slow down the evacuation time which in turn may lead to a stampede.
(3) Group movements: The movement of several evacuees as a group could also affect the evacuation process. For example, constraints in the environment such as a narrow exit can restrict the movement of a group of

evacuees. It could increase the tension perceived among group members which in turn may lead to uncoordinated movement of evacuees.

Evacuation simulation of the movement and behavior of a crowd during egress could reduce the possibility of crowd disaster [21, 22]. It is an undeniable fact that behavior of a crowd is intrinsic and could be influenced by external factors such as clogging, counter flow, narrow path and congestion. However, systematic modeling and simulation of crowd behavior could lead to minimal evacuation time and safer evacuation. Hence, it is essential to analyze the behavior of the crowd through evacuation simulation in order to provide safe and better evacuation flow during mass gatherings.

In this research contribution, crowd evacuation modeling will be focused at the microscopic level comprised of individuals, and interaction among individual levels. This is due to the basic fact that collective behavior of each pedestrian could affect the movement and behavior of the whole crowd. Game theoretic evacuation models have also been proven to be an effective model to study the crowd dynamics in terms of individual interactions that are entailed in microscopic models [23]. Consequently, in recent years a number of game theory oriented research contributions have been proposed to model crowd behavior during evacuation scenarios. Basically, game theory offers efficient computational models to make meaningful and robust decisions among interacting agents.

Game theory for evacuation modeling was initiated by Lo et al. [24] for the problem of selection of exits during a typical evacuation scenario. Competitive behavior among agents has been studied by assuming that the evacuees tend to be selfish in a non-cooperative game. One of the drawbacks of the model lies in the assumption that all evacuees need to be rational during the fire evacuation scenario. However, in a real fire evacuation, most of the evacuees tend to panic. Ehtamo et al. [25] have presented an exit selection model for evacuation based on evacuees' best response.

Another interesting work on studying crowd behavior during evacuation has been proposed by Bouzat and Kuperman [26]. The authors have utilized game theory coupled with lattice gas models in order to analyze characteristic features of pedestrians, viz. cooperative and defective behaviors confined to an indoor evacuation scenario. Their results indicated that under certain conditions, cooperators could evacuate more rapidly due to mutual cooperation. Research work proposed by Heliövaara et al. [27] and Schantz and Ehtamo [28] considers a spatial evacuation game, where the evacuees interact with their nearest neighbors by choosing either patient or impatient strategic options. Two games are discussed viz.: Prisoners Dilemma and Hawk-Dove, which depend on how far the evacuees are located from the exit. Further the evacuees choose their best response strategies depending upon observing the previous strategies chosen by their opponents. Other related work on evacuation modeling and simulation via game theory can be found in [23, 29, 30, 31, 32].

In contrast to previous work, this paper aims to investigate the impatient and patient agents in the process of exit congestion under uncertainty conditions via the classical social force model using simulations in continuous space. During emergency evacuation scenarios, strategies of evacuees will dynamically vary. It is a well-known fact that during panic scenarios, the disturbed crowd could evolve to new situations that could possibly lead to crowd disasters such as stampedes. In addition, it is natural that under emergency conditions, agents will not know for certain their opponents' strategies. Also, uncertainty in making decisions happen due to the dynamic changes of opponents located in neighborhoods (set of neighboring opponents). In such scenarios of uncertainty, agents will try to update their strategies based on their own common sense rules or their intrinsic behaviors. We intend to systematically investigate risk seeking, risk averse and risk neutral behaviors of agents. Research in the area of evacuation models under uncertainty is vital to provide insights in order to better understand the crowd behavior during emergency scenarios.

2. Proposed evacuation model in a continuous space

In this work, we consider analyzing the egress flow in a rectangular room of size $L \times W$ with a single door of length $1m$ located at the center of one of the walls. Further we assume the moving space and moving time in this predefined setup to be continuous and that the agents move to the desired direction according to the principles governed by the well known social force model [33]. Any location within the continuous space can be referred to by the usual (x, y) coordinate where $0 \leq x \leq L$ and $0 \leq y \leq W$. The sites with $x = L$, $y = 0$ and $y = W$ belong to the walls and cannot be occupied by agents except at $x = L$ and $(W/2 - 0.5) \leq\ y\ \leq (W/2 + 0.5)$ where the door is symmetrically located. Initially, the n agents, indexed by i, $i \epsilon I = (1, \ldots, n)$, are placed at random positions $0 < x < L$, $0 < y < W$ at time $t = 0$. Area density of an agent is set as $350kg/m^2$. The mass of an agent which is basically the product of area density and cross sectional area of an agent can be defined as:

$$m_i = \text{ area density } \times \pi R^2. \tag{1}$$

The above formulation will enable us to model the fact that different agents (pedestrians) will have different masses based on their cross section of human body. Radii of the agents are randomly generated ranging from 20 to $29cm$ as proposed by Korhonen and Hostikka [34]. The randomly generated mass of the agents range between 44 and $92kg$ per agent.

Each agent i with mass m_i would exert a surrounding force $\mathbf{f}_i(t)$ at time t and its position $x_i(t)$ has its own equation of motion:

$$m_i \frac{d^2 x_i(t)}{dt^2} = \mathbf{f}_i(t). \tag{2}$$

The force, $\mathbf{f}_i$ exerted on an agent i is given by

$$\mathbf{f}_i = m_i \frac{\mathbf{v}_i^0(t) - \mathbf{v}_i(t)}{\tau_i} + \sum_{j(\neq i)} \mathbf{f}_{ij} + \sum_{W} \mathbf{f}_{iW}. \tag{3}$$

In the above formulation (Eq. (3)), the first right hand side term models an agent's desire to reach a given preferred speed $|v_i^0|$ and to move towards the target in the direction of $\mathbf{v}_i^0$. The relaxation time parameter τ_i sets the strength of the motive force, which makes an agent accelerate towards the preferred walking speed and the change of position $\mathbf{r}_i(t)$ is denoted as $\mathbf{v}_i(t)$. The second right hand side term of Eq. (3) is the sum of all interaction forces $\mathbf{f}_{ij}$ exerted between agent-agent interactions. The third right hand side term of Eq. (3) sums the interaction forces $\mathbf{f}_{iW}$ exerted between agent-wall interactions. For a more detailed description of the dynamics of the model, see ref. [33].

In this work, we set the time step for one complete iteration for all agents as $0.05s$. Also, we assume that each agent has two possible actions: impatient and patient. The agents playing the strategy impatient tend to push forward and overtake others while those playing patient would tend to move with the crowd by avoiding physical contacts. Scientifically this can be specified as follows:

(1) Patient agents tend to avoid contacts with other agents. This is implemented by assigning a larger magnitude of repulsive forces and characteristic length of repulsion for the patient agents.

(2) Patient agents accelerate slower than impatient agents to their preferred speed. This is realized by increasing the individual relaxation time τ_i for the patient agents.

Relevant to the agents' behavior as described above, we set the relaxation time parameter to 0.4 or $0.5s$. Also, the repulsive force is set to 30 or $40N$ and the characteristic length of repulsion is set to 0.4 or $0.5m$ depending on the agents's behavior. Also, the repulsive force and the characteristic length of repulsion for agent-wall interaction is set to $500N$ and $0.1m$ respectively. The utilized constant value for agent-agent interactions is set to $1200kg/s^2$, whereas the constant value for agent-wall interactions is set to $2400kg/ms$. These constants denote the obstruction effects encountered during the physical interactions. We set the preferred speed $|v_i^0|$ to $1.2m/s$. The values utilized in this work intend to reduce the distance kept among agents since this work emphasizes evacuation during emergency scenarios where it is often observed that agents tend to walk closely and push each other (agents tend to overlap over neighboring agents during a packed crowd motion).

3. Proposed spatial evacuation game

Each agent has its own estimated evacuation time, T_i as defined by

$$T_i = \frac{d_i}{\|v(\mathbf{r}, t)\|}, \tag{4}$$

which depends on the distance between an agent and the exit, d_i and local speed of agent, $\|v(\mathbf{r}, t)\|$:

$$\|v(\mathbf{r}, t)\| = \frac{\sum_j v_j}{n}, \tag{5}$$

which is the mean speed of the agents around the central location $\mathbf{r}$ of agent i at time t. Agents within a skin to skin distance of less than $80cm$ to agent i are considered in Eq. (5), thus, v_j refers to the speed of an agent at time t, while n refers to total number of agents around the considered area at time t.

We perceive the crowd evacuation process as an evacuation game that is played with the objective to reduce the evacuation time. At each time step, the agent interact with its nearest neighbors. All the conflicting neighboring agents are identified and solved according to certain rules which will be defined shortly. Thus, the winners of the conflicts and the agents who are not involved in conflicts with their neighboring agents move to their desired positions. The simulation ends when all the agents have finally evacuated the room.

In order to solve the conflicting agents, at first we need to find the conflicting neighbors. The Moore neighborhood and Von Neumann neighborhood are the widely utilized neighborhood systems. Moore neighborhood comprises eight cells surrounding a central cell on a two-dimensional square lattice, while the latter embraces the four cells orthogonally surrounding a central cell on a two-dimensional square lattice. However, both are utilized in a discrete space. Neighborhood representations and relationships in a continuous space have been proposed by Heliövaara et al. [27] where the neighborhood of each agent is classified as an area around them which is a skin to skin distance of less than $40cm$. Keeping the fact that agents in a realistic environment will not usually compete with agents behind them, the following neighborhood rules have been defined:

(1) The central distance between agents i and i_c is less than $1.02 \times r_{i(i_c)}$, while $r_{i(i_c)} = r_i + r_{i_c}$ is the sum of the radii of the conflicting agents. Here an assumption is made that at least there are two conflicting agents. We represent i_c as the agents other than i in the scenario (analogous to the complement of i).

(2) The angle Θ between agents i and i_c is less than or equal to 130° as shown in Fig. 1. We assume for simplicity that agents tend to target towards reaching the center of the exit. Based on this assumption the angle Θ between agents has been determined. The angle Θ is calculated using:

$$\Theta = \cos^{-1}\left[\frac{a^2 + d^2_{i(i_c)} - b^2}{2ad_{i(i_c)}}\right]. \tag{6}$$

The agents i_c are considered as agents behind if Θ is more than 130°. The intuition is that an agent will not pose a conflict to agents who are behind him/her. However, agents behind need to wait until they may end up with conflicts with the agents in front of them.

Then, taking into account the interaction of neighboring agents between i and i_c, the mean estimated evacuation time of these neighboring agents is defined as $T_{i(i_c)} = \frac{T_i + \sum_{i_c} T_{i_c}}{1+n_{i_c}}$, where n_{i_c} refers to the number of neighboring agents for i. In cases where the neighboring agents tend to interact with each other, we need to solve the conflicts so that only one winner will be able to move. The winner can overtake other agents and reach the desired position

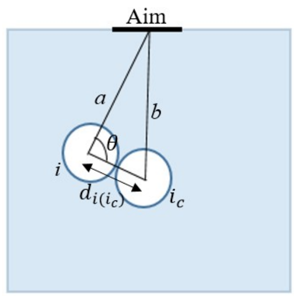


Figure 1: Angle between conflicting agents. ($d_{i(i_c)} = \|\mathbf{r}_i - \mathbf{r}_{i_c}\|$) is the center of mass distance between agents i and i_c)

and gain the utility by reducing his estimated evacuation time by Δt, while the loser(s) will remain in the current location and lose the utility where the loser's estimated evacuation time will increase by the same quantity Δt. As a result, the cost of each winner agent will get reduced to an utility that amounts to $\Delta u(T_{i(i_c)})$ and the cost of each looser agent(s) increases by the same amount.

For each step taken by an agent, the distance d_i between the agent and the exit eventually gets reduced by Δd. We define $\Delta d = \|v(\mathbf{r}, t)\| \times \Delta t$ where $\|v(\mathbf{r}, t)\|$ is the local speed of an agent i as defined in Eq. (5). Δt is set to be a constant value of $0.8s$ which is the appropriate time for each step taken by an agent. Then, we define the difference in estimated evacuation time of conflicting agents for each step as $\Delta u(Ti(i_c)) = \frac{\Delta d}{|v_i^0|}$ where $|v_i^0|$ refers to the preferred speed of an agent. When there is an empty space available, the winner of the conflicts will try his best to utilize his preferred speed in order to move to that empty space. This justifies the fact that we have deployed the preferred speed instead of the local speed of an agent in calculating the cost function $\Delta u(T_{i(i_c)})$.

In game theory terms we refer a patient agent as a cooperator (C) and that of an impatient agent as a defector (D). We have defined the rules that will enable us to decide the winner of the conflicts as follows:

(1) For the case of a conflict with n_{def} defectors and n_{coop} cooperator(s) where $n_{def} > 1$, $n_{coop} \geq 0$, the defectors will try and push in order to move. As a result of this conflict one of the defectors will be able to move while the rest of the defector(s) and all the cooperators would remain at the same location. Due to the equiprobable chance available in getting to the next move by the defectors, the payoff for the defectors is to gain the utility by reducing the cost of $\frac{\Delta u(T_{i(i_c)})}{n_{def}}$. Besides that, the defectors will face a conflict cost which could cause some energy loss or possibilities of getting injuries or time delay in movements or loosing some favourable positions in the pedestrian space. Here, conflict cost is denoted by the time delay t_d where $t_d > 0$. When the defectors try and push with each other in order to move, there will be a little delay in time. Thus, the payoff for the defectors is to gain the utility by reducing the cost of $\frac{\Delta u(T_{i(i_c)})}{n_{def}} - t_d$.

Table 1: Payoff Table for a typical 2×2 Evacuation Game (x: number of neighboring defector(s) to current agent i, y: number of neighboring cooperator(s) to current agent i, s_m refers to payoff in row m while o_n refers to payoff in column n)

	o_1	o_2
	xD, $yC(x \geq 1, y \geq 0)$	$0D$, $yC(y \geq 1)$
s_1 (D)	$\frac{\Delta u(T_{i(i_c)})}{x+1} - t_d$	$\Delta u(T_{i(i_c)})$
s_2 (C)	$-\Delta u(T_{i(i_c)})$	$\frac{\Delta u(T_{i(i_c)})}{y+1}$

While the payoff for the cooperator(s) is to lose the utility by increasing the cost of $-\Delta u(T_{i(i_c)})$.

(2) For the case of a conflict with n_{coop} cooperators, $n_{coop} \geq 1$ and one defector, the defector will be able to move while all the cooperators will remain at the same location. The payoff for the defector is to gain the utility by reducing the cost of $\Delta u(T_{i(i_c)})$. Whereas, the payoff for the cooperator(s) is to loose the utility by penalizing the cost to $-\Delta u(T_{i(i_c)})$.

(3) For the case of a conflict with n_{coop} cooperators, $n_{coop} > 1$ and no defector, no winner is selected. Even though there are no winner and loser(s), the payoff is set equal to all cooperators as the conflicting agents will move together with the crowd based on social force model. Therefore, the payoff for the cooperators is set to gain the utility by reducing cost of $\frac{\Delta u(T_{i(i_c)})}{n_{coop}}$.

Based on the aforementioned assertions, a 2×2 game matrix is built as shown in Table 1. The payoff shown in Table 1 accounts only for the row wise agents since all the other agents will get an identical payoff for similar type of interactions. When a strategy is chosen by the agents in the row, the payoff received for the concerned agent is given in the corresponding cell of the matrix. Since we have utilized a small time step ($0.05s$) which is about more than 10 times slower when compared to one complete movement of an agent (the preferred speed of an agent in normal and emergency situations is in the range $0.6 - 1.5m/s$ [33]), the winner of the conflicts will again win in the next conflict provided the conflict is between identical neighbors as with previous neighbors.

4. Decision strategies amidst uncertain scenarios

Each agent intends to play the aforementioned game with its nearest neighbors except the agents who are behind. Previous studies [26, 27, 28] have assumed that agents will update their strategy based on their opponents' strategies. However, it is natural that under emergency conditions (where panic prevails), agents will not know for certain the strategies of their opponents. Also, uncertainty in making decisions arises due to the dynamic changes exhibited by the neighboring opponents. In such scenarios of uncertainty, agents will try to update their strategy based on their own rules or instinctive behaviors. Here, a parallel update scheme [35] is utilized where strategies of all agents are updated simultaneously at each time step. We have utilized the parallel update scheme in order to describe the behavior of evacuees more realistically than a shuffle or fixed update order scheme. In the shuffle or fixed update order scheme, for an evacuation simulation with n agents, a simulation round will take a total of n time steps. This means that it will take about n time steps in order for a particular agent to update his strategy, which is not realistic.

We investigate three types of agent behaviors viz., risk seeking, risk averse and risk neutral. Risk seeking or risk loving can be perceived as the particular attitude of agents where they look for gaining maximum utility under uncertain scenarios anticipating fast evacuation. Risk seeking agents who seek to achieve the best results will attempt to utilize the maximax criterion in selecting the strategy that maximizes the maximum available payoff. Maximax rule is defined by

$$a_i^{max} = \arg max_{r \epsilon \{s_1, s_2\}} u_r \; \textit{iff} \; u_r \epsilon \arg max\{u_{s_1}, u_{s_2}\}, \tag{7}$$

where a_i^{max} refers to the chosen strategy, u_{s_1} and u_{s_2} represents the expected utility for the strategy indicated in subscript and u_r refers to the maximum expected utility of a row wise agent who opts for strategies C and D.

Risk averse denotes the behavior of the agents where they seek the best out of the worst results. This type of behavior is applicable to agents who seek for the alternative that maximizes the minimum achievable payoff. Risk averse agents would look at the worst possible outcome of each strategy and then select the strategy that gives the highest outcome. Thus, risk averse agents will utilize the maximin rule which is defined by

$$a_i^{min} = \arg max_{r \epsilon \{s_1, s_2\}} u_r \; \textit{iff} \; u_r \epsilon \arg min\{u_{s_1}, u_{s_2}\}. \tag{8}$$

This rule will enable them in selecting the strategy that maximizes the minimum available payoff. Here, u_r refers to the minimum expected utility of a row wise agent who opts for strategies C and D. In simple terms, risk averse agents prefer to choose the outcome which is guaranteed to minimize their losses.

Risk neutral behavior refers to agents who prefers to take conservative decisions during uncertain scenarios where only very little information is known about the preferences of other opponents. The minimax regret rule is more applicable to this type of agents. Such agents earns regret by failing to choose the best decision. The following steps will be taken in order to find the optimal result based on minimax regret criterion:

(1) Determine the best utility over all strategies (maximum utility in each column strategies).

(2) Determine the loss for each strategy as the difference between its utility value and the best utility value.

Table 2: Opportunity Lost Payoff Table for a 2×2 Evacuation Game (x: number of neighboring defector(s) to current agent i, y: number of neighboring cooperator(s) to current agent i, $s_{m_{new}}$ refers to payoff in row m and $o_{n_{new}}$ refers to payoff in column n)

	$o_{1_{new}}$	$o_{2_{new}}$
	$xD,\ yC(x \geq 1,\ y \geq 0)$	$0D,\ yC(y \geq 1)$
$s_{1_{new}}$ (D)	$max\{u(s_k, o_1)\} - \left[\frac{\Delta u(T_{i(i_c)})}{x+1} - t_d\right]$	$max\{u(s_k, o_2)\} - \left[\Delta u(T_{i(i_c)})\right]$
$s_{2_{new}}$ (C)	$max\{u(s_k, o_1)\} - \left[\Delta u(T_{i(i_c)})\right]$	$max\{u(s_k, o_2)\} - \left[\frac{\Delta u(T_{i(i_c)})}{y+1}\right]$

(3) For each strategy, find the maximum loss over all strategies.
(4) Choose the strategy that has the minimum of maximum losses.

Steps 1 and 2 can be formalized as

$$s(s_m, o_n) = max\{u(s_k, o_n)\} - u(s_m, o_n). \tag{9}$$

The payoff table for minimax regret is based on "lost opportunity" as explained in Table 2. Stages 3 and 4 which deploy the options defined in Table 2 can be formalized using

$$a_i^{min} = \arg min_{r \epsilon \{s_{1_{new}}, s_{2_{new}}\}} u_r \ \textit{iff} \ u_r \epsilon \arg max\{u_{s_{1_{new}}}, u_{s_{2_{new}}}\}, \tag{10}$$

where $s_{1_{new}}$ and $s_{2_{new}}$ refers to the new payoff for strategies cooperate and defect respectively based on Table 2.

5. Simulations

In this section, we present our computer simulations with respect to the models proposed in the previous sections (Sections II to IV). For our simulations, we consider a rectangular room of size $18m \times 17m$ which consists of a single door of length $1m$ located at the center of one of the walls. The pedestrian room space at the range of locations $x = 18$ and $y = 0$ to $y = 17$ belong to the walls and cannot be occupied by agents except at $x = 18$ and $y = 8$ to $y = 9$ where the door is symmetrically located. Initially, 200 agents are placed at random positions in the range $0 < x < 17$, $1 < y < 16$ at time, $t = 0$. First we simulate the population comprising of homogeneous agents where all of the agents are either risk seeking or risk averse or risk neutral before we consider the simulation of a heterogeneous population.

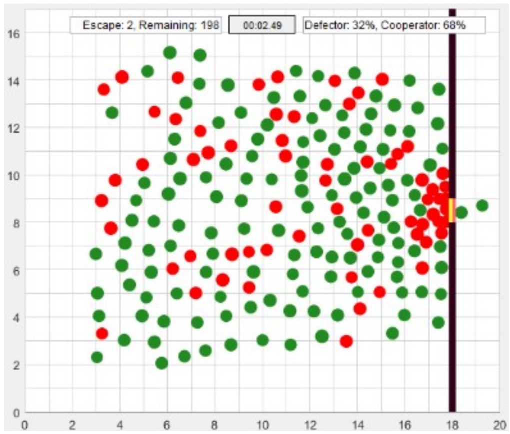
5.1. Simulation results with a homogeneous population

Here, we perform simulations with a homogeneous population in order to study the outcomes of each behavior of agents, viz. risk seeking, risk averse and risk neutral in choosing either a defect or cooperate strategy when confronted with emergency conditions especially when the preference of other neighboring agents are unknown. In these experiments we assume that the behavior of the agents is fixed. In other words, the agents' behavior is unchanged throughout the simulations. This aids us to better study on how these agents update their strategies based on a particular mode of behavior and subsequently how this affects the egress flow.

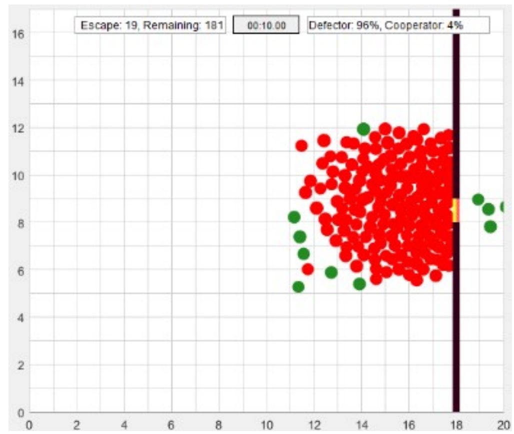
First, we consider a population in which all the agents possess risk seeking behavior and adopt the maximax rule. This type of agents are considered quite adventurous as they aim to achieve best results, anticipating fast evacuation. Fig. 2 shows snapshots of the agents' positions at different time steps t throughout the evacuation process for a time delay (conflict cost) t_d of $1.2s$ with 25% of the initial population opting to play for the *defect* strategy and that of the rest 75% opting to play for the *cooperate* strategy. We study the evolution of agents' strategies for a time frame of $35s$ as a result of various time delays caused by conflicts in an evacuation simulation. Typical results pertaining to evolution of cooperate and defect strategies are portrayed in Fig. 3. Fig. 4 shows evolution of defect strategy alone with various initial proportion of agents who chose a defect strategy corresponding to various conflict time delays (t_d). From these results, it can be observed that risk seeking agents prefer defect strategy irrespective of the amount of conflict time delays. Hence, maximax gain strategy conforms to agents acting as defectors. Since other neighboring agents maximax strategy also have been chosen to be defectors, mutual defection yields the maximax gain equilibrium for risk seeking agents. This seems to be an equilibrium solution that maximizes each agent's greatest hopes.

Next, we consider a population which comprises of only risk averse agents. This type of agents can be considered as moderate since they seek the best of the worse possible results, which is the maximin rule. Similar to experimental conditions of risk seeking agents, we study the evolution of risk averse agents strategies. Typical results for evolution of cooperate and defect strategies are shown in Fig. 5. Fig. 6 shows evolution of the defect strategy alone with various initial proportions of agents who chose defect strategy corresponding to various time delays (t_d).

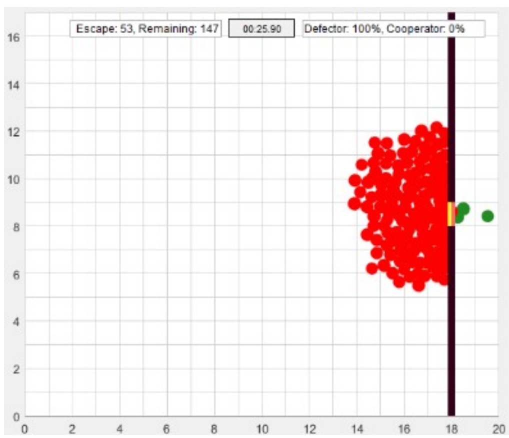
We observed that risk averse agents prefer defect strategy when the conflict time delay is less than $0.5s$. For $t_d < 0.5s$ mutual defection attains the maximin gain equilibrium since strategies of other neighboring agents maximin rule have also been chosen to be of defectors. However, when t_d is increased from $0.5s$, we observe the emergence of cooperate strategy. Thus, for $0.5s \leq t_d < 1.1s$, an equilibrium of mix strategies has been observed. Finally, when t_d is about $1.1s$ and above, all risk averse agents prefer to choose cooperate strategy which further infers that maximin gain equilibrium has attained mutual cooperation. It has also been observed that an equilibrium of risk averse agents gain strategy



(a) $t = 2.49s$



(b) $t = 10.00s$



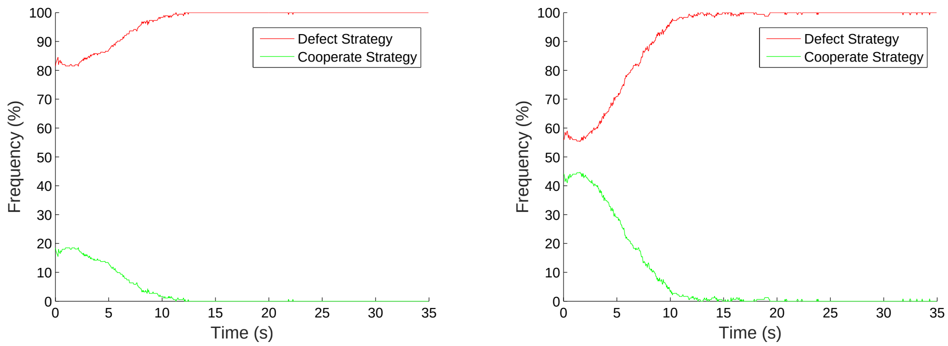
(c) $t = 25.90s$

(d) $t = 66.24s$

Figure 2: Evacuation simulation of typical risk seeking agents population for different time steps where each axes of the subfigures indicate distance in meters. Parameter used: $t_d = 1.2s$ (Red: Defector, Green: Cooperator)

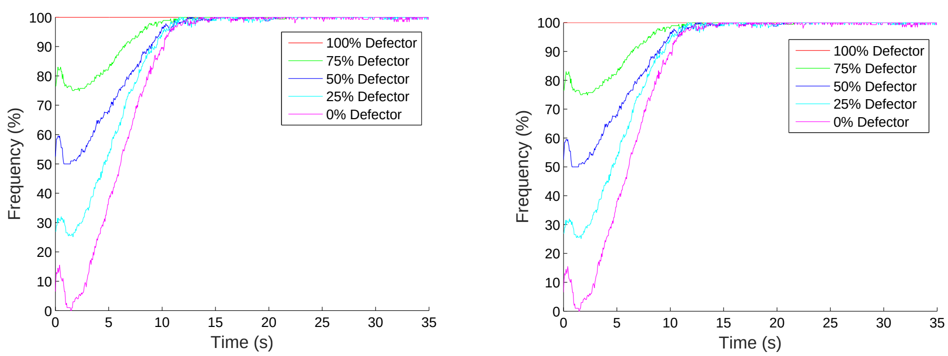
depends on the conflict time delay. Importantly, these equilibrium solutions maximize each agents security level. Finally, we study a population of risk neutral agents alone. This type of agents are basically conservative decision makers and hence application of the minimax regret rule is more appropriate. Similar to the experimental conditions of previous types of agents, we study the evolution of risk neutral agents strategies for various time variations.

Typical results for evolution of cooperate and defect strategies are shown in Fig. 7, while Fig. 8 shows evolution of defect strategy alone with various initial proportions. We observe that preferences of risk neutral agents are similar to that of risk averse agents. They prefer defect strategy when the conflict time



(a) $t_d = 1.2s$ (b) $t_d = 2.0s$

Figure 3: Evolution of cooperate and defect frequency in an evacuation simulation with all risk seeking agents

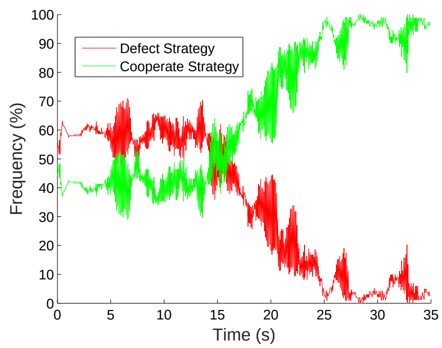


(a) $t_d = 0.3s$ (b) $t_d = 2s$

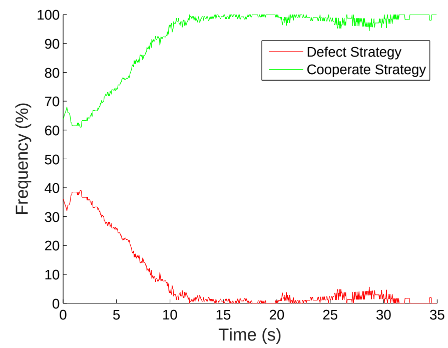
Figure 4: Evolution of defect strategy frequency for risk seeking agents with various t_d. The different colors show the evolution of the system for different initial proportions of the defector strategy

delay is less than $0.5s$. Emergence of the cooperate strategy for risk neutral agents happens when $t_d \geq 0.5s$, while equilibrium of mix strategy has been observed when $0.5s \leq t_d < 1.5s$. When the conflict time delay (t_d) is about $1.5s$ and above, all risk neutral agents prefer to opt for the cooperate strategy which in turn infers that minimax regret gain equilibrium attains mutual cooperation. Equilibrium of risk neutral agents gain strategy also depends on the conflict time delay. In fact, these equilibrium solutions minimize each agent's greatest fears.

From the above simulation results, we found that cooperate strategy emerges if and only if the population is risk averse and risk neutral. A conflict time delay of $1.1s$ is required for mutual cooperation to occur among risk averse agents



(a) $t_d = 0.7s$



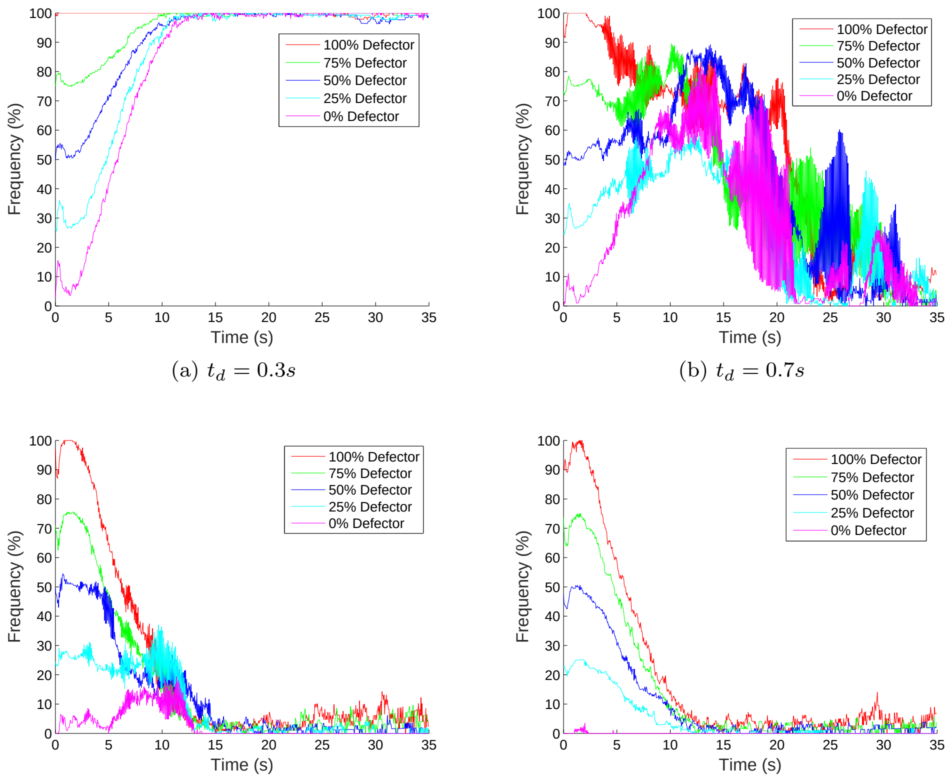
(b) $t_d = 1.5s$

Figure 5: Evolution of cooperate and defect frequency in an evacuation simulation with all risk averse agents

while it takes $1.5s$ for that of risk neutral agents. Fig. 9 show examples of 20 evacuation simulation results pertaining to these experiments. Fig. 9 also shows similar simulation results with less variations in terms of total escape time for each run thereby indicating the robustness of the proposed evacuation model.

Then, we study the mean escape time for these types of agents with respect various conflict time delays. Simulations have been repeated for 20 runs with different initial random frequencies of cooperators and defectors placed in random initial locations, by fixing the behavior of the agents. The final results for these simulations is shown in Fig. 10. It can be seen that risk seeking agents who anticipate to evacuate fast end up with slower escape times compared to other types of agents. This is owing to the fact that risk seeking agents always choose the defect strategy in all conflicts since defect strategy attains a maximum out of maximum results. For risk averse agents, as discussed earlier, when t_d is less than $0.5s$, all risk averse agents act as defectors which cause more evacuation time. Evacuation time is lesser when mix strategy of cooperators and defectors exist, while fastest escape time for risk averse agents occur when all the agents act as cooperators which is when t_d is about $1.1s$ and above. Results for risk neutral agents are quite similar to risk averse agents except that fastest escape time for risk neutral agents happen when mutual cooperation occur which is when t_d is about $1.5s$ and above. In summary, based on our simulation results shown in Fig. 10, we can observe that risk averse agents achieve faster evacuation time whenever the conflict time delay is more than $0.5s$.

In terms of evacuation time for impatient and patient agents, our simulation results are also in agreement with that of previous work [26, 27, 28]: the more the number of impatient agents, the slower the egress time. This scenario is referred as the faster-is-slower effect which happens due to the increased number of conflicts when more impatient agents tend to move straight towards the exit. This results in a clogging effect near the exit [1, 3, 36, 37, 38]. This clogging



(a) $t_d = 0.3s$ (b) $t_d = 0.7s$

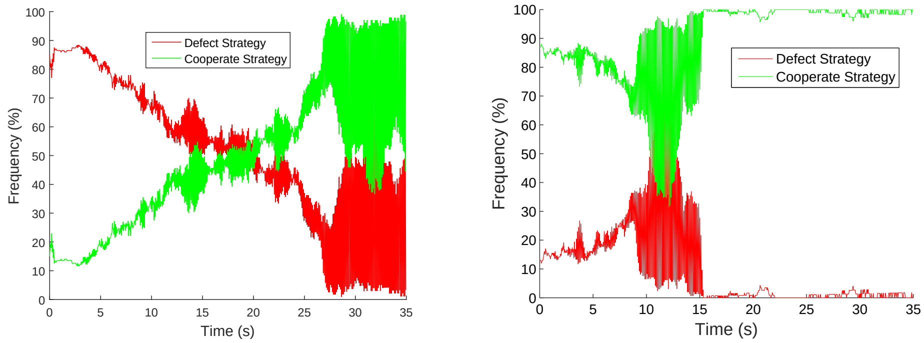
(c) $t_d = 1s$ (d) $t_d = 1.5s$

Figure 6: Evolution of defect strategy frequency for risk averse agents with various t_d. The different colors show the evolution of the system for different initial proportions of the defector strategy

slows down the total escape time. In other words, it can be inferred that faster evacuation time occurs once mutual cooperation among agents are achieved.

5.2. Simulation results with respect to a heterogeneous population

In this subsection, we perform simulations with respect to a heterogeneous population in order to study the effect of the risk seeking, risk averse and risk neutral behavior of agents towards egress. We study the mean escape time by repeating the simulations with different random frequencies of cooperator and defectors placed at random initial locations. For each of the simulations, the number of one of the agents behavior has been fixed, while the number of other two behaviors were randomly selected. The final result for these simulations is shown in Fig. 11. From the simulation results in Fig. 11, for a conflict time delay of $0.4s$, the average escape time for all types of agents has been almost similar thereby indicating the occurrences of mutual defection. For conflict time



(a) $t_d = 0.8s$ (b) $t_d = 1.2s$

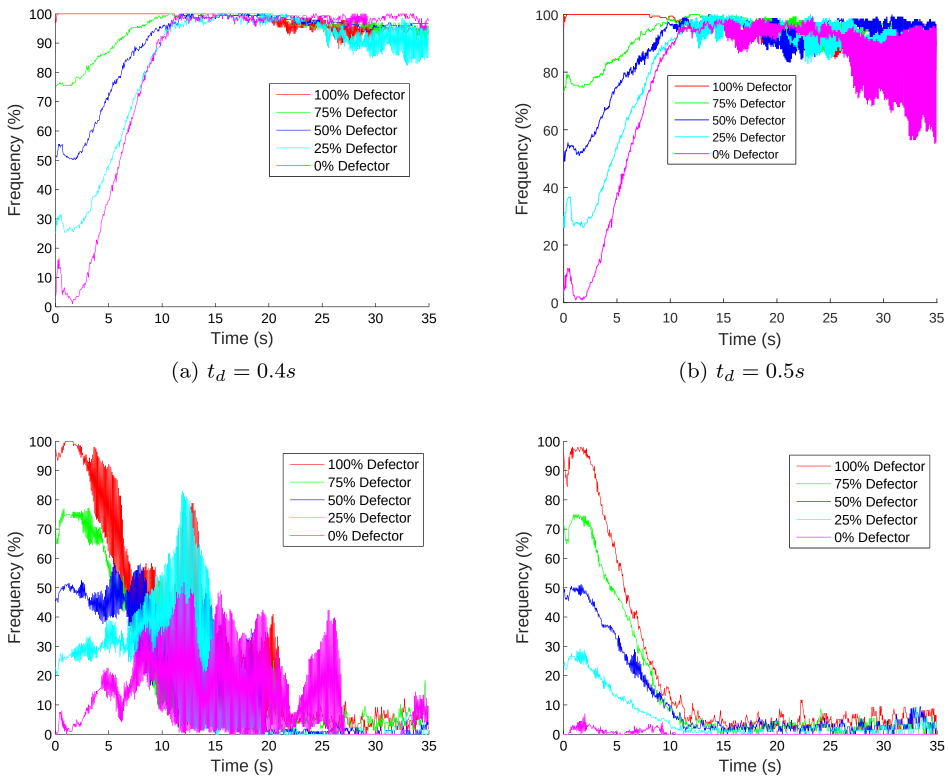
Figure 7: Evolution of cooperate and defect frequency in an evacuation simulation with all risk neutral agents

delays of $0.8s$ and $1.3s$, we observe that when the risk seeking agents population is increased, the average escape time becomes slower. In contrast, the average escape time tends to be faster when the risk averse agents population gets increased. The average escape time is almost similar when the population of risk neutral agents is increased with respect to $t_d = 0.8s$. For the case of $t_d = 1.3s$ similar results with risk averse agents' have been observed. In essence, amidst uncertainty conditions, based on our simulation results seen in Fig. 11, we can observe that a faster evacuation time is achieved when there is an increase in conflict time delays and in the population of risk averse agents.

6. Conclusions

We have systematically investigated the effect on egress under uncertainty scenarios that could possibly arise during emergency evacuations. In particular, we examine the risk seeking, risk averse and risk neutral behaviors of agents (pedestrians) using the norms of a typical game theory approach. We have simulated evacuation scenarios in a continuous space using the classical social force model, where the impatient and patient agents have been experimented with in different individual parameter settings. In summary, the main contributions of this research are as follows:

(1) Agents neighbourhood is treated in the continuous space which attempts to intuitively emulate pedestrian interactions that occur during mass gatherings.
(2) A comparative study of characteristic features of risk seeking, risk averse and risk neutral agents has been systematically analysed.
(3) Study of effect on escape time based on simulation of two types of evacuees viz., impatient and patient agents under uncertainty has been reported.



(a) $t_d = 0.4s$ (b) $t_d = 0.5s$

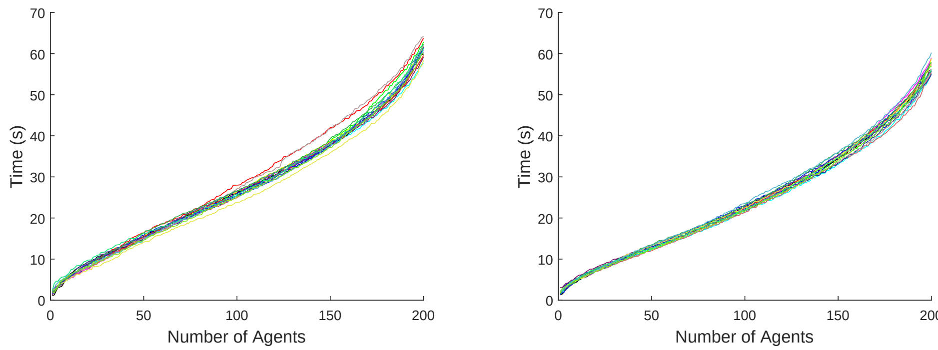
(c) $t_d = 1.1s$ (d) $t_d = 1.5s$

Figure 8: Evolution of defect strategy frequency for risk averse agents with various t_d. The different colors show the evolution of the system for different initial proportions of the defector strategy

We focused on the game-theoretic model of the interaction between the evacuees. We have set out a framework that can be used by designers of crowd control and evacuation systems. They will have to re-run our model with their specific values for parameters such as room size, repulsive force and its range, angle under which agents are in conflict, etc. Our simulations show what kind of behavior can be expected. For future avenues, we would consider to perform a detailed investigation of evacuation scenarios in rooms of different sizes, under different ranges of the force, and containing obstacles.

7. Acknowledgments

This research is supported by the LRGS Grant: 203/PTS6728001 and the RUI Grant: 1001/PKOMP/811290 awarded by the Ministry of Education, Malaysia and Universiti Sains Malaysia respectively. The first author would like to thank



(a) $t_d = 0.8s$ (b) $t_d = 1.5s$

Figure 9: Evacuation time for each of the 20 simulations of (a) Risk averse agents with $t_d = 0.8s$ and (b) Risk neutral agents with $t_d = 1.5s$

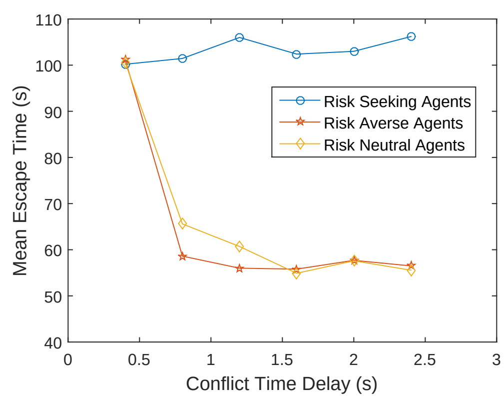


Figure 10: Mean evacuation time of 200 agents of homogeneous population related with different values of conflict time delay t_d

the International Islamic University Malaysia (IIUM) and the Ministry of Higher Education Malaysia (MOHE) for providing a PhD scholarship. The authors also thank Julian Schmidt and Alexander Späh for sharing their Panic Simulator which simulates the escape panic behavior proposed by [33].

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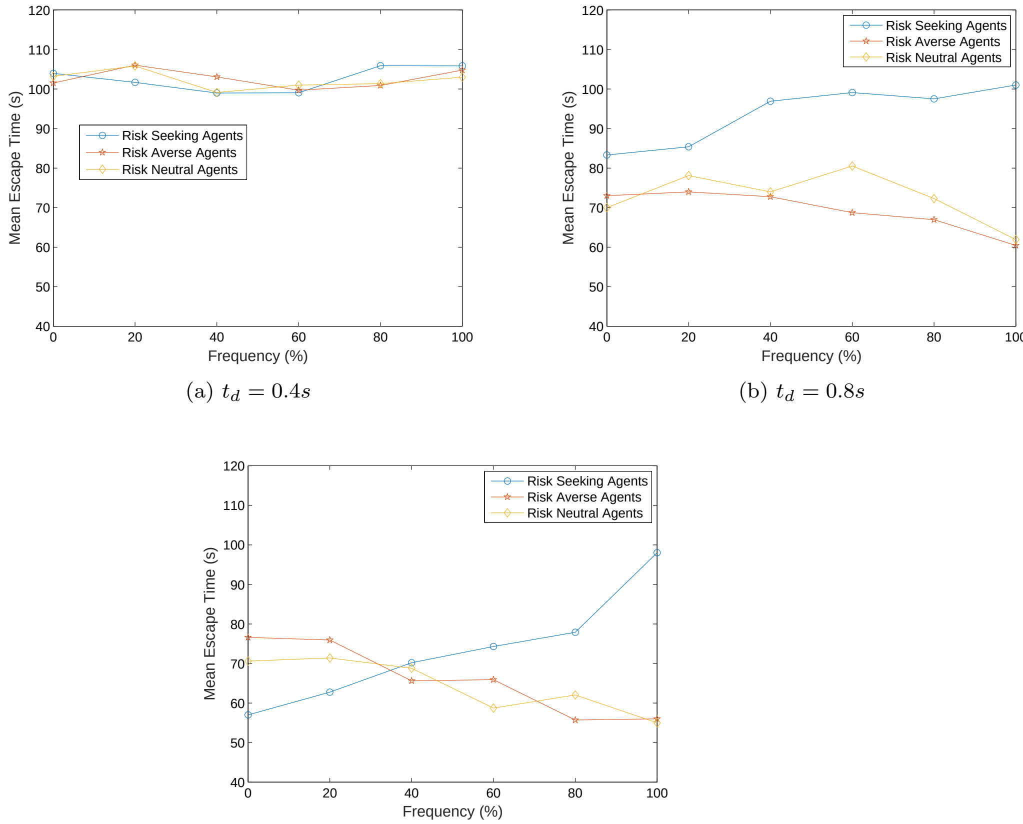

(a) $t_d = 0.4s$

(b) $t_d = 0.8s$

(c) $t_d = 1.3s$

Figure 11: Mean evacuation time of 200 agents of heterogeneous population related with different frequency proportions of fixed agents behaviors for different conflict time delay. Parameter used: a) $t_d = 0.4s$, b) $t_d = 0.8s$ and c) $t_d = 1.3s$

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