An Agent-Based Model of Crowd Evacuation: Combining Individual, Social and Technological Aspects

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ABSTRACT

Development of crowd evacuation systems is a challenge due to involvement of complex interrelated aspects, diversity of involved individuals and/or environment, and lack of direct evidence. Evacuation modeling and simulation is used to analyze various possible outcomes as different scenarios unfold, typically when the complexity of scenario is high. However, incorporation of different aspect categories in a unified modeling space is a challenge. In this paper, we addressed this challenge by combining individual, social and technological models of people during evacuation, while pivoting all these aspects on a common agent-based modeling framework and a grid-based hypothetical environment. By simulating these models, an insight into the effectiveness of several interesting evacuation scenarios is provided. Based on the simulation results, a couple of useful recommendations are also given. The most important recommendation is not to use potential field indicating the exits dynamics as an exit strategy particularly for a spatial complexity environment.

CCS CONCEPTS

• **Computing methodologies** → Model development and analysis; *Agent / discrete models*; Distributed simulation.

KEYWORDS

Evacuation; Agent Based Modeling; discrete-time simulation; emotional vs. rational agents; physical vs. social influence; NetLogo.

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1 INTRODUCTION

Emergency evacuation is often associated with crowd panic leading to herding (or stampedes). It usually happens as a consequence of irrational behavior (due to fear, hassle, dominance, etc.) of a few emotionally intense individuals. Herding is the main reason of deaths during emergency evacuation [34]. Not much can be done during such an incidence reactively; unless, we are able to analyze various aspects of population (density, genre, mood, etc.), environment (geometry, number and placements of exits, possible bottlenecks, external factors such as weather, etc.) and technology to preempt strategies of evacuation in a combinatorial way. Agent-based modeling (ABM) [19, 30] and simulation is one of the modeling method that can be utilized to achieve it.

Salient features of ABM – autonomy, reactivity, pro-activity and social interaction – make this method a natural choice for scenarios requiring autonomous and adaptive participating agents [18]. Structurally, an evacuation strategy should utilize all the exits while ending in distribution of population across the exits well-balanced (in terms of time), which is a perfect application of flow control [13, 14]. However, at an individual level, an agent must be considered as a social entity [23] (not a particle) having its own preferences, biases and emotions, and capability to adapt according to changing dynamics of the environment. This dichotomy can only be resolved if we are able to model most relevant aspects of human adaptive decision making, while trying to find the conditions which lead to more structurally balanced evacuation.

Another way of putting the above is from modeling method perspective. One way of modeling such systems is to have focus on global flow consideration [7]. Another way is to have focus on local interactions only [32]. Specific to evacuation, there are models which only emphasize on efficiency of various structural layouts of the environment [31].

Models have been proposed which only focus on collectives (at a global scale) [27], including, clogging [24], bottlenecks [16] and faster-is-slower [11] effects. However, modeling of an evacuation situation solely based on Physics has been under criticism [2, 21, 22]. The reason is that individual and localized (social) decisions happening at the local scale manifest into a global patterns [15]. Therefore, a more deeper insight into these collective effects cannot be attained without having knowledge about decision-making at a local scale [23]. In particular, the understanding on emergence of global patterns in relation to rules of local decision making of individuals poses more questions than answers.

Our research more than a decade old now has been trying to fill this gap. The work presented in this paper is inspired form the work of Wang et. al. [29] and its extension presented in our previous work [34]. With focus on modeling for local interactions, we have focused on the question of rationality vs. emotionalism of individuals in a social context, a phenomena well-researched in social, psychological and economics domains, but, relatively unexplored in the domain of evacuation modeling and simulation. We have also presented a novel model of embedding of technological

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influence (an extended social influence) in the decision-making of evacuees and to analyze it's effect on evacuation efficiency.

The model presented in [29] differentiates between two sub-populations, typed "emotional" and "rational". The model exploits the dynamics usually observed during a violent evacuation scene, representing "emotional" behavior as behavior of mimicking others and "rational" behavior, which is entirely opposite of it. The model proposed in [34] questioned Wang et. al.'s notion of rational behavior and attached it with the notion of "panic", hypothesizing that a rational agent would only do opposite to mimicking others, if its is in panic. To capture the panic situation, a formal spatial model was incorporated with the homophily-based social model.

However, the above model only takes individual characteristics of an evacuee into consideration. Hence, the decision about what exit to choose, is only based on the dynamics of a limited neighborhood. In this paper, we propose to extend this model so that it incorporates the environmental dynamics as well. Environmental dynamics are realized by using the potential field concept, which is a collective of mechanisms of (exit) event capturing i.e. content, spreading of the content and its influence on the population of agents.

The proposed extension actually corresponds to the concept of "guided assistance". In our previous work, we used a device named as LifeBelt to provide vibro-tactile assistance to the users wearing it, hence guiding them towards the safe exit(s) [9]. The device was particularly designed for environments with poor visibility due to blackout or smoke, a potential situation that may occur during a natural hazard or a technological failure [10]. The device was able to actuate appropriate vibra elements based on what was sensed about flow at various distant exits. The locomotive behavior (short-range mobility), thus, was produced as a combined effect of coarse directional guidance and social pressure in the neighborhood. An extensive experimental trial helped us develop models of mobility in the presence of social and cognitive load when evacuation happens in a ambient-assisted environment [36]. The model developed has enough fertility. It is being experimented in an industrial setting [20]. It has been used for a city scale evacuation [35].

Here, in this paper, we have further extended the conceptual framework of (technologically-)assisted evacuation in the presence of social as well as individual aspects. The proposed model performs a marriage between the lessens learned from our work on "ambient-assisted" evacuation (as discussed in the paragraph above) and "game-theoretic" individualistic utility framework presented in [34]. More specifically, the proposed model captures all the essential ingredients of information dissemination and adoption (potentially using today's impressive technological landscape), which augments spatial model of identifying a panic situation and assisting rational agents making a more fruitful decision during evacuation.

The rest of the paper is organized as follows. Section 2 outlines the background and contribution of the paper. Following it, section 3 provides a detailed account of models. This includes basic space and time model and the simulation setup. Also, in this section, the model of decision-making – individual, social and technological – is detailed. Following the models, section 4 is about simulation setup and results. The paper is concluded in section 5.

2 BACKGROUND AND CONTRIBUTION

2.1 Background

Crowd evacuation is one of those phenomena for which an evidence about human behavior is hard to get. In most cases, the questions about efficiency of egress from a troubled environment are answered using behavioral theories and behavioral patterns observed in other domains, such as crowd mobility, navigation and way finding. In addition to that, the dimensions across which such an inquiry can be extended are numerous, such as infrastructural modalities (smoke and visibility, building design, signage, exits designs etc.), crowd dynamics (crowd density, lanes and flows, population diversity etc.), information (vision and voice, ICT enabled infrastructure, availability of information through social network or local connectivity, etc.), individual decision-making (emotions, rationalism, panic behavior, etc.), and collective effects (leader-following, herding effect, peer effect etc.). Although the title of the paper marginalizes it, but, in addition to individual, social and technological, we have also incorporated layout of the environment in our model, thus trying to include as many dimensions stated above in our model.

With respect to infrastructure, authors in [25] have analyzed the importance of building design particularly the presence of physical ques (building signage) for egress efficiency. Evaluation of spatial features in evacuation at the scale of city is done in [8]. There are many other models [10, 35] which consider quite complex environments and structures to elaborate significance of this aspect. But, the model presented in this paper does not particularly focus on this aspect. However, we still represent difficulty imposed by complexity of the structure of the building by introducing structures which differ with each other with respect to complexity.

The behavioral theories about crowd mobility dynamics are of three types. In contagion theory [3], an individual in crowd has no significance. It becomes a part of the crowd (as that of a particle in a fluid flow) and the forces of crowd direct its actions. This essentially leads to a panic situation in which an uncontrollable herd develops. Although, this concept has been used in many crowd evacuation studies – such as [13] and its applications [33] –, however, this theory is refuted by many researchers, and emergence of panic is mostly considered a myth rather than a reality [6].

Emergent norm theory [5] is conceptually different from contagion theory in the sense that it builds on social rather than physical sciences. It focuses on the behavior of the individuals which may differ. Interactions between individuals happen at a local scale which collectively transform into emergence of a global behavior. Many models [28] are based on this theory and have been modeled using agent-based modeling paradigm [35]. Emergent norm theory is the building block of many agent-based evacuation models that model individual behavior. As a consequence of local interaction of agents, a global behavior emerges on which the agents have no control. However, at the same time, the global outcome influence the agents again (in the form of a feedback loop). Functionally, similar kind of influence is also applied on individual agents, but the phenomena observed is at social level. Within that social boundary, all the agents get this message and change their activity accordingly.

The third theory is known as structuralism. This theory is entirely opposite of emergent norm theory. Rather than having focus on individuals, it focuses on individual structures. Hence, it gains information about social or macro information and considers changes which would result at the micro level due to these. Usually, the system dynamic approach is used in this domain [12]. Typically, global behavior is modeled as a domino effect to the smaller system components. This approach has also been used for the modeling of building evacuation [4, 26].

Last two approaches are more closer to panic situation during evacuation because they use individualistic approach; a single person or a group. What we feel more natural is to use these two theories in combination. To illustrate it, we take the model presented in [4] as an example. Authors in this paper have used a system dynamic model for panic evaluation, the input for which is anchored into social structures. Hence the whole structure is in panic or not panic, and responds to it at the same level (each individual in a group adhering to behavior against the group panic). Hence, their mechanism compromises the requirement of individualism. Yes, the individualism may be extended to include social groups as well, however, to us, it compromises the origination of panic, which is by many can be a contribution of even a single individual in a crowd. Therefore, the mechanism of an individual panic should be purely local. This then corresponds to evacuee's ability to move under surrounding pressure. In addition to this conceptual understanding, our model of panic evaluation is also evidenced using an experimental study [9].

The consequence of this situation of being influenced by local panic can then be translated into a decision-making model. Towards this, [29] presented a co-evolutionary model of strategy and game structure. The population used in the model was divided into two sub-populations based on individuals being either "emotional" or "rational". Each individual in the emotional sub-population tends to select the same behavior as most of other individuals nearby. However, each individual in the rational sub-population tends to select a different behavior than most of other individuals nearby. They developed a simple two player game and by carefully setting corresponding payoffs, they studied different phenomena, such as conditions leading to extinction of one sub-population and conditions necessary for a herding effect.

We [34] extended Wang model arguing that "it is probably irrational that an agent will be "rational" if it takes a decision contrary to the decision taken by most of the individuals in its range of influence. If an agent is smoothly moving towards a desired exit, why should it deviate from its course of action. For example, if an agent has observed that an exit is the nearest and the agent is sailing at a satisfied pace towards that exit, it seems inappropriate to deviate the agent from path towards that exit just because it is rational." Hence a more realistic model was proposed based on the following concept: "If an agent is productively covering the route towards an exit, no deviation takes place. However, as it faces difficulty in doing so, it allows switching the exit. This difficulty is termed "panic" in this work." In this paper, we replicate this mechanism to compare it with the proposed model.

2.2 Contribution

Our previous model formally reported in [34], only considers the individualistic characteristics and decision is only based on the dynamics of a limited neighborhood. We propose to extend this model so that it incorporates the environmental dynamics as well. The model relating panic (or not panic) with decision-making is based on Wang model [29]. We extend this model as follows.

Similar to [4], we take external (wider) influence as a determining factor of decision-making. But this influence is not social. It is structural and mediated by ambient assistance. Nevertheless, the influence reaches to all the agents in different form, which corresponds to *suggested* reflection of *both spatial and event knowledge* [26]. The effect of it on the decision-making of agents is not group level, but only individual. This spatial influence is further negotiated towards a decision based on whether the agent is in panic or not.

Environmental dynamics are realized by using the potential field concept. The potential is defined by its "content", "spread", and "influence". The *content* of the potential field is an event, reporting arrival of an individual at an exit. Before an individual escapes (and subtracted from the population), it announces the exit that it is escaping from. This information then *spread*s out and reaches to other individuals using a proximity based spreading mechanism. The spreading is accompanied by the notion of *intensity*, which captures the distance the information has covered - more intensity means less distance and less intensity means more distance. The intensity of information also depletes, thus fading away with time. When this information reaches to an individual it has an *influence* on the individual. The exit having more intensity of the influence is then used to make a decision using a payoff based decision tree.

Technologically, the "spread" of this potential is supported by devices that we usually carry these days. However, its influence is gone when the person carrying the device leaves its location. Since, other people gets effected by the decisions taken by the person carrying the device, the influence becomes a resident property of the space. That is why potential field is implemented as a spatial feature.

The potential disseminated this way augments spatial model of identifying a panic situation and assisting rational agents making a more fruitful decision during evacuation.

3 MODELS

3.1 Space and Time Model

Before detailed description of the decision making model, it is essential to explain space and time model. The simulator used is called as NetLogo's [30], which has been used to simulated emergency egress [1]. This work uses a two-dimensional hypothetical square-shaped simulation world comprising of cells of equal size. The size of the world is 51×51 cells; hence, a total of 2601 cells and each cell is represented by a xy-coordinate point. Mobile agents reside on top of the cells and they are capable of using the information available at the underlying cell and that of neighboring cells and/or agents to make their decisions. The simulation operates in discrete times (time-stamps); in which each agent gets its turn at all atomic time-stamps. The agents make decisions sequentially, i.e., incremented state of the world is used. NetLogo's built-in engine provides fair chances to the agents due to random sequencing of agents at each time-stamp.

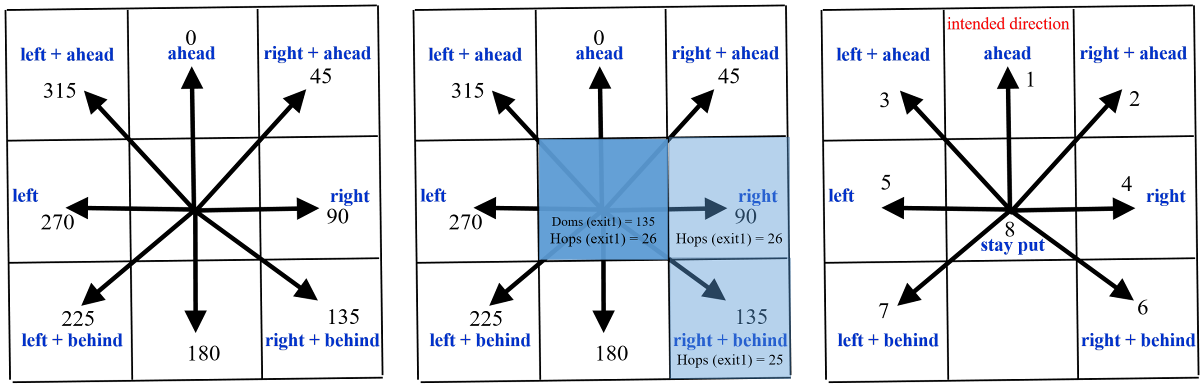

Figure 1: Left: Moore's Neighborhood of cell at the center of size 1. The textual descriptions of directions assume an agent at the central cell whose current heading (orientation) is towards the cells at angle 0 (the reason why it is labelled "ahead"). Middle: Spread of floor field. Information about exit1 to the cell in the center comes from cell at the right and behind and cell at the right. Since the hops to exit1 reported by the cell at the right and behind is less than what is reported by the cell at the right, direction to reach to exit1 is 135 (towards the source cell) and hop count is 1 more than source cell. Right: The next cell selection strategy explained. Directional preferences of an agent with intended direction labeled '1'.

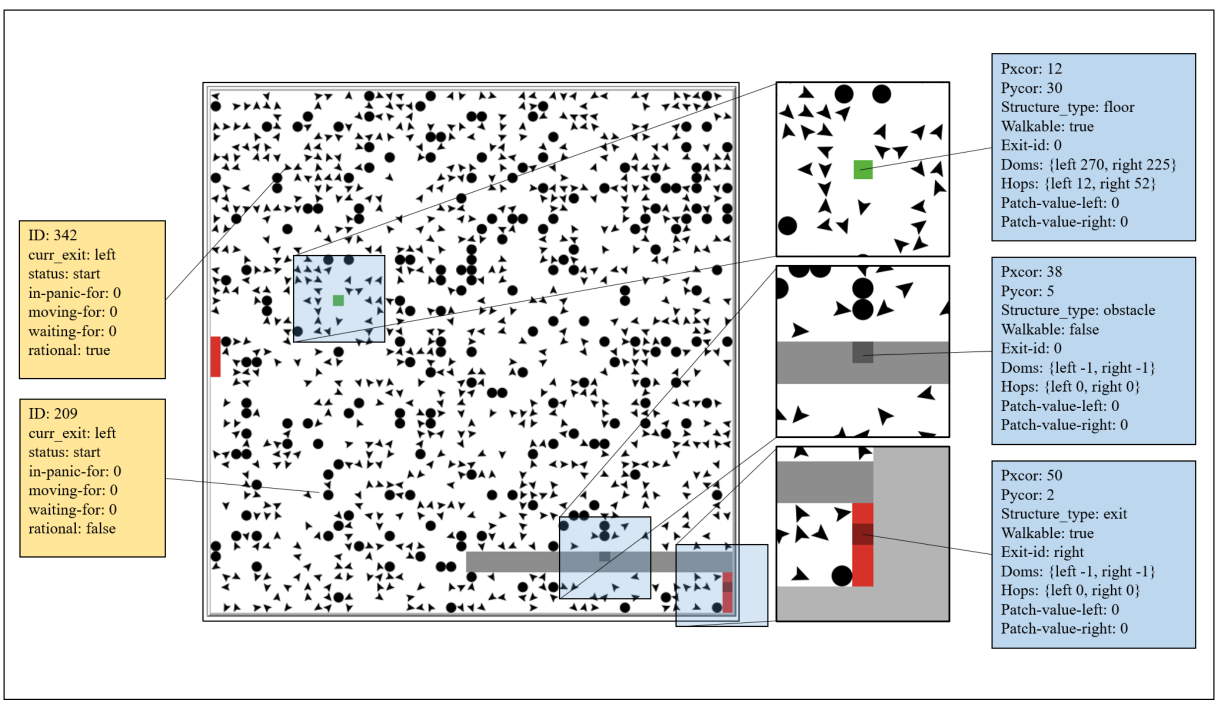

Figure 2: Simulation Setup having 1000 agents. This setup has a hidden exit (the right exit).

The simulation world is first setup with a floor field. As a result, each cell knows about: (i) (shortest) distance of each of the exits with a field name *Hops*, and direction towards each of the exits corresponding to the shortest distance with a field name *Doms*. The neighborhood used is Moore's neighborhood [17] - a cluster of eight adjacent cells around a cell. Figure 1 (left) shows neighborhood of size 1 of the cell in the center and directions (as used in Netlogo). The spread of floor field starts from exits and disperses outwards following a neighborhood based interaction. A cell receiving an information from one of its neighbors, checks the hop count (an accumulating counter) of the exit it started from. If it is less that its current value, the old value of hop count is replaced by this value. The direction is set to the direction towards the source cell. Figure 1 (middle) shows a localized example of floor field spread.

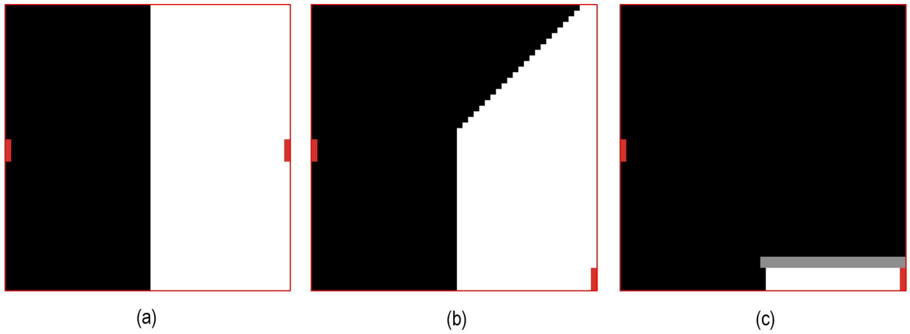

Figure 3: Three geometric variations of two exits shown in red. (a) Symmetric: the number of cells closer to the left exit (shown in black) is equal to the number of cells closer to the right exit (shown in white). (b) Asymmetric: the number of cells closer to the left exit (shown in black) is not equal to the number of cells closer to the right exit (shown in white). (c) Hidden: a limited number of cells are closer to the right exit (shown in white) due to its invisibility because of an obstacle, for example a wall (shown in gray).

A cell in Netlogo is called patch. Hence, the default variables names are prefixed by patch x-coordinate (Pxcor) and patch y-coordinate (Pycor). In the environment shown in Figure 2 the cell in green thus have the following configuration: Pxcor = 12, Pycor = 30, Doms = left 270, right 225, and Hops = left 12, right 52. The agent sitting on its patch, through the floor field, knows that the distance to left exit is 12 hops, and distance to right exit is 52 hops. This is the shortest distance and navigating towards these exit would require the agent to move to cell at 270 (for left exit) and 225 (for right exit). However, in addition to the floor field, the information from its neighboring cells and agents is also used by an agent to make a decision.

The square space adopted has two exits. Figure 3 presents three cases of exit distribution based on the nearest exit measure. These distributions are called symmetric, asymmetric and hidden. The initial exit measure (the nearest exit) act as the initial belief of the agents while routing towards an exit.

Different patch types completes the environment details. These are:

- normal: A normal patch is walkable and its type is floor (see green patch in Figure 2).
- obstacles: The patches that act as obstacles. The floor field spread does not passes through them, hence, Doms and Hops of these patches only have default values. An obstacle patch is not walkable and its type is obstacle (see gray patch in Figure 2).
- exits: The patches that are exits. The floor field spread start from these patches, hence, Doms and Hops of these patches only have default values. An exit patch is walkable and its type is exit (see red patch in Figure 2). These are the only patches having exit_id other than 0; having name of the exit (left or right).

3.2 Agents' Variables and Model of Microscopic Moves

The following three cases are used for random distribution of agents before starting a simulation:

(1) Sparse: 500 agents with density of 0.2 per cell.
(2) Medium: 1000 agents with density of 0.4 per cell.
(3) Dense: 1500 agents with density of 0.6 per cell.

Rational agents in each case are 5% of the overall population. The rest of them are Emotional. Figure 2 distinguishes these two types of agents. An emotional agent is represented with a triangular shape, whereas rational agents are circular shape. All agents have IDs, and curr_exit based of nearest exit from floor field of the patch they are residing (initially). They also have some state variables which would be explained later.

The microscopic next cell selection strategy adopted in this work is based on the concept of Moore's neighborhood [17]. In this strategy, an agent can choose one of its 8 neighboring cells depending on the direction in which it is traveling. However, it uses the strategy shown in Figure 1 (right) to choose the desired cell may already be occupied by another agent. In this case, the agent adopts a strategy to choose an unoccupied cell, if the desired cell is already occupied. Figure 1 (right) shows a dial towards the intended direction labeled with '1'. If the cell in this direction is occupied, the agent will choose the direction labeled with '2', and so on. The strategy is based on empirical evidence explained by Ferscha and Zia [9].

The next cell selection mechanism is initiated when an agent knows the direction to move under the influence of one of the strategies (decision making models) presented in the next subsection.

The following state variables are used to record the locomotive behavior of the agents. The default values are all zeroes.

- moving_for is an incremental index recording continuous mobility of an agent. If an agent intends to move to a cell, and the desired cell is not occupied, then after the move, the moving_for value will be one more than the value in previous iteration. When the value of moving_for is incremented, the two indices described below are reset to 0.
- waiting_for is an incremental index recording continuous state of an agent not able to make a move. The current waiting_for value, if incremented by 1, also resets the moving_for value to 0.

		Player 2 (a random neighbor)					
		Behavior 1	Behavior 2	Behavior 1	Behavior 2	Behavior 1	Behavior 2
Player 1 (a decision-making agent)	Behavior 1	1	1*	1**	0***	0	1
	Behavior 2	1*	1	0***	1**	1	0
				not in panic		in panic	
		Emotional		Rational			

Table 1: The panic game: *exit change with probability 0.1, if in_panic_for > 0, **exit change with probability 0.1, ***exit change with probability 0.9.

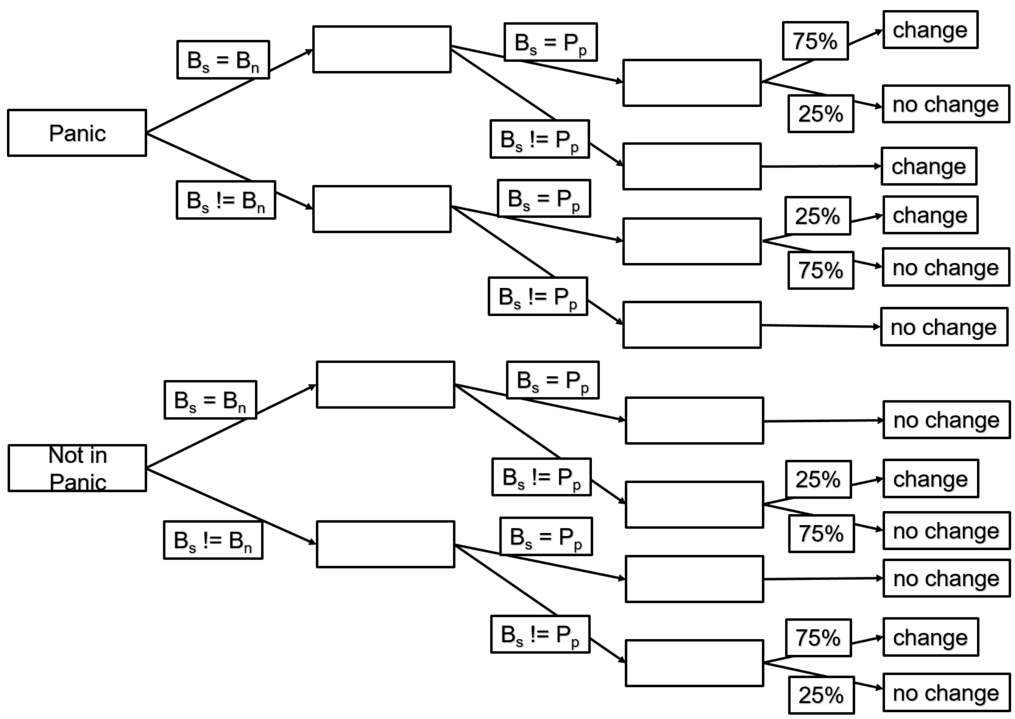

Figure 4: The panic game extended to incorporate exits potential used with surrounding influence.

- in_panic_for records the agent being in panic for continuous sequence of iterations. The waiting_for value is used to set an agent in "panicking" state if the waiting_for crosses a threshold value. waiting_for and in_panic_for variables are reset to 0, when an agent starts moving again.

Finally, *state* of an agent provides an interface between locomotion and exit strategies; initially set to START. More about agents' states w.r.t. simulation is presented in the next section.

3.3 Decision Making Strategies

Decision making strategies let the agents choose one of the two exits based on which one is nearest (individual bias) or local (social) influence or under the influence of exits potential (technological). Correspondingly, these are three strategies: strategy 1 being the base case, strategy 2 being our previous published work and strategy 3 is what is proposed in this paper.

3.3.1 Nearest Exit (S1): The agents in all cases start with the nearest exit; i.e. one of the two exits with least value of Hops. This information is available at each patch, enabled through the mechanism of floor field spread, executed at the simulation setup. This is a static strategy and used to compare it with game theoretic approaches, which allow dynamic changing between exits.

3.3.2 The Panic Game (S2): This strategy is based on game theory. Player 1 (termed as Agent) is the one who is making a decision, and Player 2 (a random neighbor from Moore's neighborhood) is the influencer.

For an emotional Agent, if the behavior of the neighbor is same as its own behavior, then the payoff is maximum and the Agent retains its behavior that is keep moving towards the current exit. The payoff remains maximum, even when the behavior of random neighbor is opposite of the agent behavior - that is why these agents are "emotional". However, there are 10% chances that an

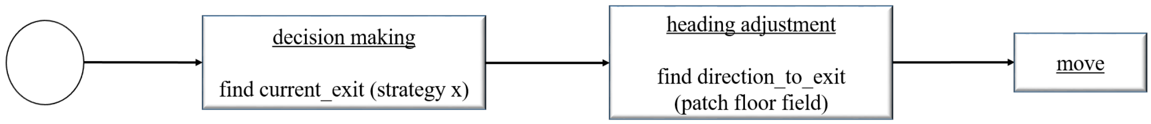

Figure 5: High level simulation procedures.

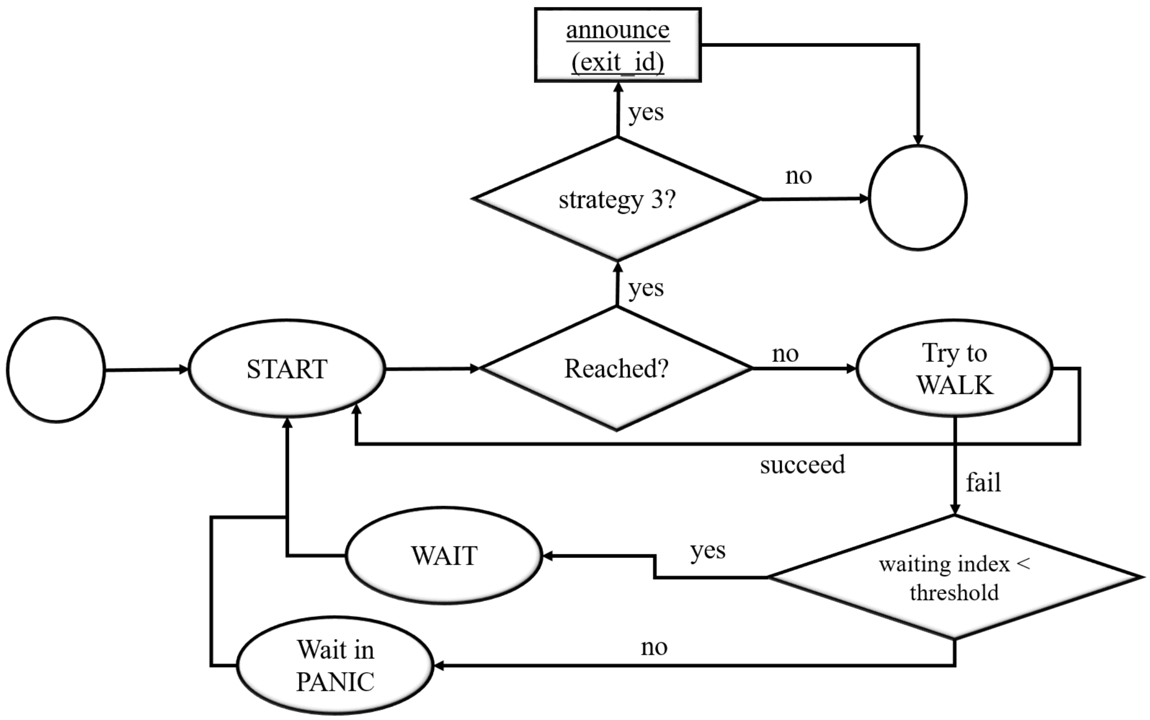

Figure 6: Details of procedure move and related transition system.

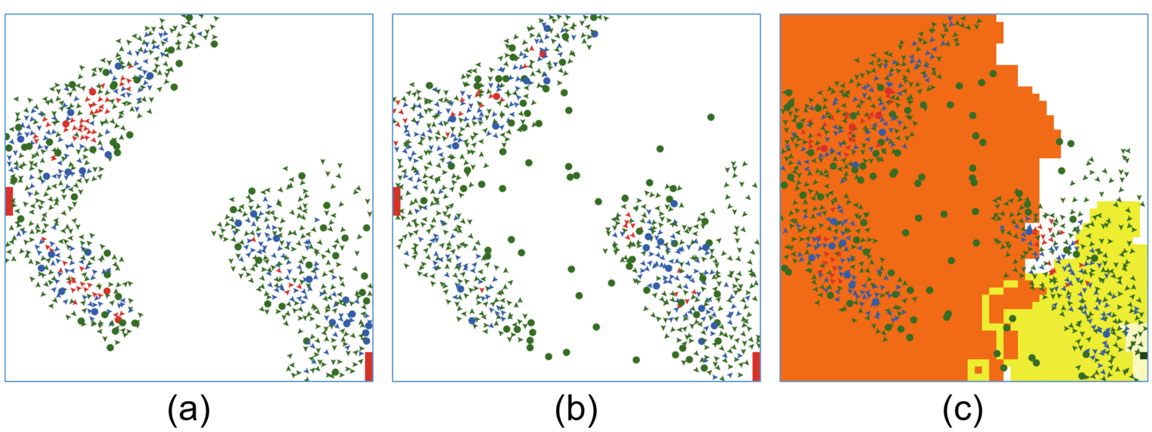

Figure 7: Screen-shots of random simulation outcome at iteration 25, in case of (a) all agents only going to the nearest exit, (b) rational agents under the influence of locality driven rationality, and (c) rational agents following the proposed model.

agent may change its behavior, if in_panic_for > 0 which ensures random deviation. This means that the game is not really played by emotional agents. It is the rational agent who plays the game. The strategy for a rational Agent is dependent on whether it is in the state of panic or not. If the Agent is not in panic, it will be a source of strengthening its belief on current behavior if the random neighbor has the same behavior represented as maximum payoff in this case. However, there are 10% chances that the Agent may change its behavior, thus ensuring a random deviation. On the other hand, it will be a source of weakening the Agent's belief on the current behavior if the random neighbor has opposite behavior represented by a minimum payoff in this case. However, there are 90% chances that the Agent may change its behavior leaving 10% chances for random deviation.

If the Agent is in panic, we argue about entirely opposite behavior, in which same behavior represent minimum payoff. This direct the Agent to change the behavior but strictly this time. Similarly, if the behavior of the random neighbor is different from Agent's own behavior, the Agent will strictly retain its recent behavior.

The Panic Game is explained in the Table 1.

3.3.3 The Panic-Potential Decision (S3): Like the above model, the decision of an agent differs depending on if the agent is in panic or otherwise. The model is only applicable to rational agent, and emotional agents keep following the nearest exit. In addition to the above model, the proposed model is also based on two conjunctures presented in [26]. These are:

- The spatial change has a negative effect when detouring occurs due to a lack of knowledge.
- The spatial change has a positive effect when the exit utilization is balanced.

In Figure 4, we detail the model.

The current behavior (left or right exit) is represented as B_s. The rational agent who is making a decision, randomly chooses a neighbor; where current behavior of the neighbor is represented as B_n. Lets relative potential of the patch underneath the agent is represented as P_p. Since we have two exits, the value of P_p would be either left or right, depending on which one is greater, thus, representing more influential exit.

If agent is not in panic, and B_s is equal to B_n, then we can consider the agent quite satisfied. Now if B_s is also equal to P_p, then the agent has nothing to worry about. No change is required in this case. However, if B_s is not equal to P_p, then it has something to worry about, but still two factors are in its favor ((i) no panic, (ii) neighbor's influence). Hence, it would only make a change (switching the exit) with a probability of 25%; with a probability of 75%, it would adopt no change.

If agent is not in panic, and B_s is not equal to B_n, then we can consider the agent has something to worry about. Now if B_s is equal to P_p, then the agent is satisfied as its own behavior and the potential, both pointing to the same exit. No change is required in this case. However, if B_s is not equal to P_p, then it has a real worry, because both neighbor and potential are against the current behavior. Hence, it would make a change (switching the exit) with a probability of 75%; with a probability of 25%, it would adopt no change.

Before we detail the behavior of an agent in panic, its worthwhile to state that the agent is already in a worry due to panic. If agent is in panic, and B_s is equal to B_n, it may exaggerate its worry due to neighbors also moving to current exit, which seems counterproductive. Now even if B_s is equal to P_p, this may not help a lot. Hence, it would make a change (switching the exit) with a probability of 75%; with a probability of 25%, it would adopt no change. However, if B_s is not equal to P_p, then it would definitely change its exit, due to all factors going against the current exit.

If agent is in panic, and B_s is not equal to B_n, then there is something to worry. Now if B_s is also equal to P_p, then the agent may decide to change the exit but with little motivation; it would make a change (switching the exit) with a probability of 25%; with a probability of 75%, it would adopt no change. However, if B_s is not equal to P_p, then this can act as a satisfaction, thus resulting in no change.

The difference between these three strategies is presented with visualization of the simulation space in Figure 7. Agents' position at iteration 25 is shown in all three situations: (a) all agents only going to the nearest exit, (b) rational agents under the influence of locality driven rationality (whereas emotional following the nearest exit), and (c) rational agents following the proposed model (whereas emotional following the nearest exit), where agents represented with circles are rational agents and others are emotional. Different colors of the agents represent different states (will be detailed later).

When comparing Figure 7 (b) with (a), it is evident that quite a few rational agents are moving from (nearest) right exit to the left exit under the influence of locality driven rationality. Whereas, the proposed strategy shown in Figure 7 (c) in hinted by different colored potential field spread out of exits and expected to increase the efficiency of evacuation.

4 SIMULATION

As mentioned before as well, the simulation world is a bounded grid of cells. Agents reside on top of these cells and change their positions under the influence of exit decision that is made. Repositioning and decision making happen at each time stamp of the simulation and for all the agents. An agent exits using one of the exits, it is not part of the simulation world any more. The termination condition of simulation is number of agents still in the simulation space. Hence, at each time stamp, at first, a procedure counts total number of agents in the environment. If it is zero, the simulation stops. Otherwise, the procedure of decision making lets an agent find the current exit to follow. The decision making strategy **x** is one out of three explained before. As the exit is selected, the procedure of heading adjustment adjust the direction of the agent based on floor field available at the cell level. After this an agent tries to move, which has its own dynamics (detailed below). Thea above mentioned sequencing of procedures is shown in Figure 5.

The procedure move (the mobility module) in the form of a transition system is shown in Figure 6. START is the initial state. First an agent checks if it has reached to an exit. In this case, the process of mobility ends. Except that in case of strategy 3 (the proposed strategy), it also announces the usage of the exit it has reached to, which spread out as a potential field. If the agent has

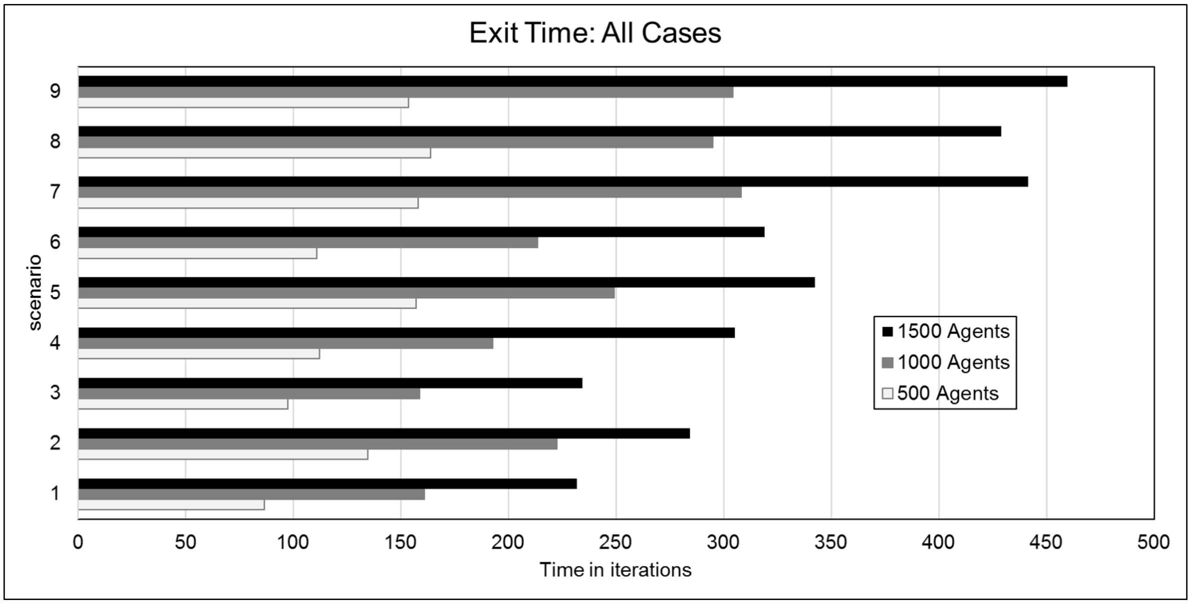

Figure 8: Exit Time: All cases.

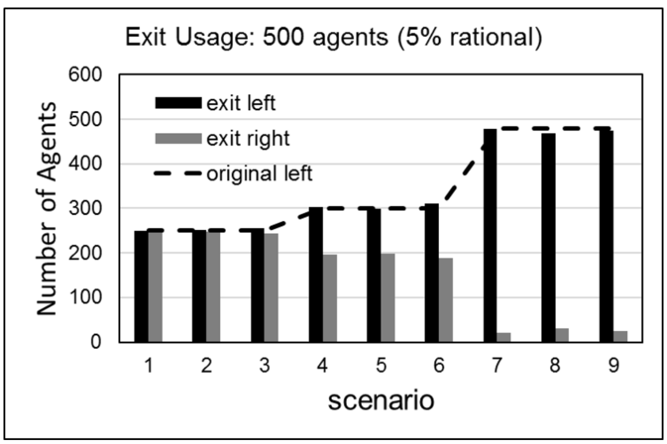

Figure 9: Exits Usage: 500 agents.

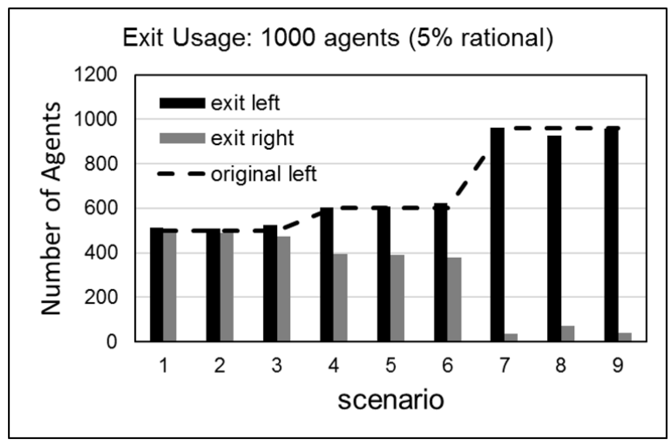

Figure 10: Exits Usage: 1000 agents.

not reached to an exit, it tries to re-position (WALK). If is is able to do it (succeeds), it moves and go back to starting state. If it fails to do so, it may enter into WAIT or PANIC state depending on waiting index. If waiting index is less than threshold it waits (does nothing and increments waiting index). If waiting index is greater than threshold it waits but in a state of panic. After increasing the indexes, the agent comes back to start state and tries to walk again the next iteration.

4.1 Simulation Results: Quantitative Analysis

Table 2 lists the scenarios / cases. Each of these scenarios is simulated with different populations of agents – 500, 1000, and 1500 – where percentage of rational agents is 5% of the population. The Simulation results are evaluated based on the following quantitative measures:

(1) Exit Time: the number of iterations (simulation ticks) needed so that all agents exit through exits.
(2) Exit Usage: the distribution of the number of agents exiting through different (two) exits.
(3) Agents in Panic: the peak value of number of agents in panic during the simulation.

4.1.1 Exit Time. As the number of agents increases, obviously the exit time also increases as shown in Figure 8. A comparative analysis of scenario 1 to 3 reveals that scenario 2 performs worst in all agent populations when compared to scenario 1 and 3. This means that strategy S3 performs better than S2 and comparable to S1, in spite of S1 presumably the best (in terms of exit time) due to

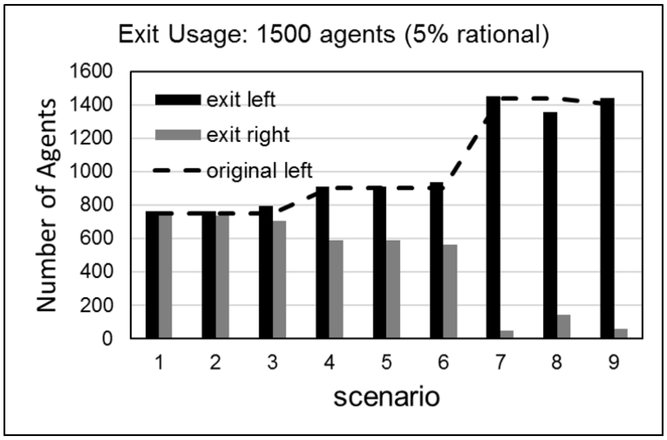

Figure 11: Exits Usage: 1500 agents.

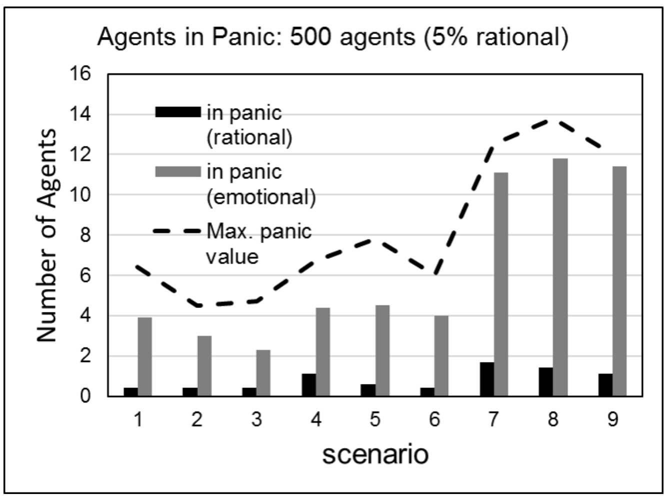

Figure 12: Agents in Panic: 500 agents.

Scenario	Strategy	Environment Type
1	S1	1
2	S2	1
3	S3	1
4	S1	2
5	S2	2
6	S3	2
7	S1	3
8	S2	3
9	S3	3

Table 2: Simulation Scenarios / Cases

all agents directing to the nearest exit irrespective of their panic and emotional state. In our last paper [34], we also observed the same fact. However, we emphasized that for a herding crowd, the factor of panic in people is more important factor than exit time. The new model with focus on exitting dynamics also (incorporated through

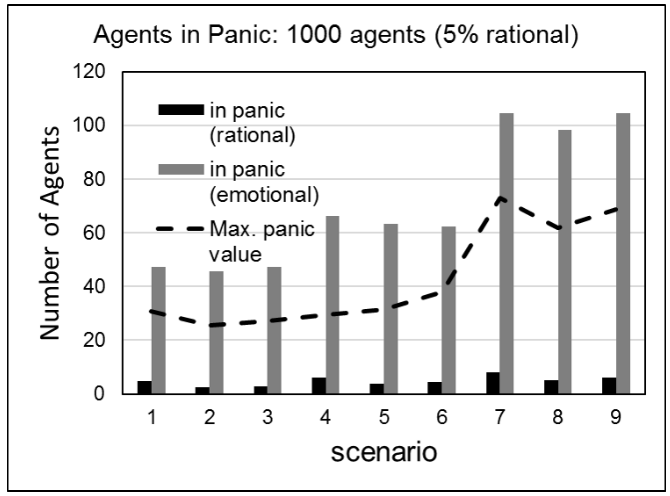

Figure 13: Agents in Panic: 1000 agents.

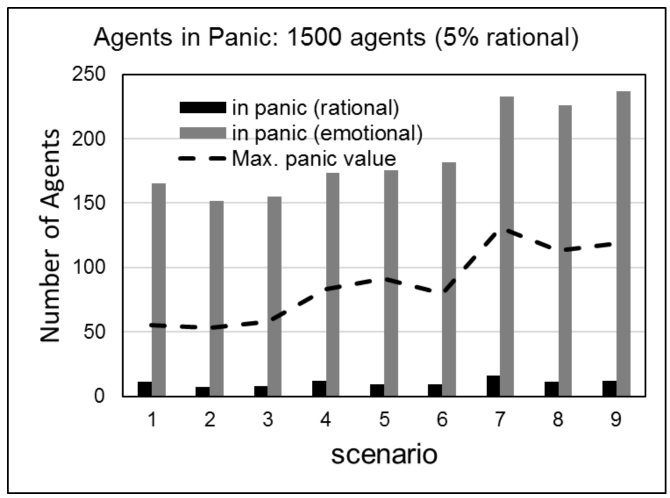

Figure 14: Agents in Panic: 1500 agents.

potential field) solves this problem as well. However, this is only true for geometrically simpler environments. In a more challenging spatial geometry, S2 performs better than S1 and S3 both (observe scenario 7 to 9 in Figure 8).

4.1.2 Exit Usage. Quantitatively, the reason of the exit time being good or bad is due to change of agents' exit – good if many agents change their exit from left to the right (given the geometric considerations of the space). This is typically true in case of scenario 8 in case of 1500 agents (compare exit usage graphs shown in Figure 9, Figure 10 and Figure 11). Original number of agents started with the left exit are shown with the dotted line in all these graphs. The columns then show the number of agents actually ending up at left or right exit when the simulation ends. There is a significant change in scenario 8 in case of 1000 and 1500 agents when comparing original left with that of actual left, which explains the reason of better exit time of scenario 8 in case of 1500 agents.

4.1.3 Agents in Panic. One of the purpose of the model proposed in this paper is to reduce the panic in the crowd. This actually always happens in case of sparse population (see Figure 12), which is not exactly the case in case of moderate and dense population (Figure 13 and Figure 14). In all these graphs, there is a dotted line representing the maximum panic value acquired by *any* agent during the simulation. Most of the time, this value corresponds to the total number of agents which once or more went into the state of panic – both rational and emotional – any time during the simulation. But, this can be a useful measure representing a lonely agent whose panic is unusually high than the others.

In case of sparse population (500 agents), the proposed strategy helps reducing the overall panic in agents in all three environments. This is evidenced in Figure 12. Whereas the above is not evidenced in case of more denser populations (see Figure 13 and Figure 14). Specifically, this is true for more complex environments. For more regular environments, the panic in the system for S2 and S3 is comparable.

4.2 Simulation Results: Qualitative Analysis

The quantitative results about exit time and usage have the following implications. As the spatial complexity of the environment from where people are evacuating increases, it is recommended not to use potential field indicating the exit dynamics as a strategy for evacuation. It means that for a regular geometries (like symmetric and asymmetric exits in big halls etc., without any narrow corridors and hidden structures), people herding towards *visible* exits with or without rationalism would not make much difference in terms of exit time. However, if agents behave rationally, they must realize that they would exit in the same time at population level. Given they are aware of it, this would prevent them to go into panic state which can be the cause of many other dangerous situations. At the administrative level, directional guidance can be provide by using technology (announcements and exit signs) based on exit dynamics and what would be its effect at specific locations, leaving the decision of acting rationally or emotionally to the people.

The results about population panic are more intuitive. As the geometry of the environment is more complex, and coupled with more denser population, would generate more panic. It must be reiterated that panic is the result of a person not able to move (proceed towards one of the exits) for a longer period of time. That is the reason, the issue of panic becomes severe in the with more people and with the complexity of the environment. Hence, the only way to reduce the panic is not to let the facilities get overpopulated in all circumstances. A disaster may initiate merely based on some people panicking due to congestion (even in the absence of any external calamity).

5 CONCLUSION

An agent-based model providing a framework to explore individual, social and technological aspects of crowd evacuation is proposed. Many scenarios are evaluated, which led to the following recommendations:
Recommendations:

- As the spatial complexity of the environment from where people are evacuating increases, it is recommended not to use potential field indicating the exits dynamics as a strategy for evacuation.
- In more spatially complex environments, there is no remedy for reducing the panic, even if potential field is used to indicate the exits dynamics. This is in accordance with accepted notion of panic, that is panic is a resident property of an individual and cannot be controlled. The only recommendation is not to let the facilities get overpopulated, particularly in case of structurally complex environment.

Limitations: Although the behavioral assumptions about people in panic during a herding situation have an underpinning on behavioral theories, empirical evidences and models progression, but building blocks of human behavior and environmental dynamics used to develop the model in this paper are not explicitly verified.

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