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Modelling Multi-Exits Large-Venue Pedestrian Evacuation with Dual-Strategy Adaptive Particle Swarm Optimization

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ABSTRACT Modeling individual and crowd behaviors is the basis for evacuation research, which is essential to reducing casualties under emergency conditions in large venues. This paper focuses on the pedestrian evacuation of large-scale venues with multiple exits, and proposes an improved pedestrian evacuation model which uses a novel dual-strategy adaptive particle swarm optimization algorithm with affinity propagation clustering. Compared with the traditional models, the proposed model is demonstrated to have a better performance in simulating pedestrians' herding behavior in panic situations, especially when not familiar with the environment, as i) individual heterogeneity is considered and affinity propagation clustering is used in population division to simulate the process of people spontaneously gathering into swarms; ii) A dual-strategy updating scheme is designed to balance the cognition difference between the leaders and the agents in the swarm; and iii) Adaptive control of parameters is used to simulate the human-surrounding interaction and psychological fluctuates when the evacuees are moving towards exits. Numerical examples are provided, in which evacuation of a rectangle venue with multiple exits is simulated to demonstrate the effectiveness and practicality of the proposed model. Moreover, the influences of pedestrian velocity, characteristics of exits, and leader movement on evacuation are analyzed. Experimental results show that the movement of leaders is different from other evacuees and the parameters of doors, such as width, quantity, and location all have a great influence on evacuation time.

INDEX TERMS Pedestrian evacuation, Crowd behavior, Particle swarm optimization, Cellular automaton

I. INTRODUCTION

EMERGENCY evacuation and pedestrian dynamics have drawn the attention of researchers from many different areas, with the goal of understanding and mitigating the risks of scenarios when people are exposed to natural disasters (e.g. earthquake, fire, flood, etc.), or threatened by terrorists in enclosed public spaces such as museums, libraries, and stadiums. Take the fire evacuation as an example, the statistics of the U.S. Fire Administration indicate that about 1,319,500 fires occurred in American in 2017, which led to 3,400 deaths in total and 14,670 injuries. Long evacuation time and high panic degrees may appear when disasters happen in large public places, especially when they are not familiar with the environment. Stampeded pedestrians caused by emergency may result in greater casualties. While well-developed emergency plans and proper guidelines will certainly have a positive effect on improving the efficiency of evacuation and reducing damages, a good understanding of pedestrians' dynamics under emergency evacuation is the basis of evacuation management. Simulation of pedestrian evacuation enables researchers to mimic the entire evacuation process under various emergency evacuation conditions, and will directly support the development of emergency evacuation plans.

Research on pedestrian evacuation simulation can be categorized into seven main categories, according to their modeling approaches as shown in Table 1. Early works on e-vacuation modeling focused on the physical features of the building. However, this kind of model ignored the initial state and individual differences of pedestrians, which resulted in an inaccurate estimation of the evacuation time, such as [1], [2]. With the advancement in computer computation capabilities, the more complicated computation can be handled. Both features of buildings and response of pedestrians under different situations were taken into account, such as network flow models [3], [4], agent-based models [5], [6], game theory models [7]-[10], cellular automaton models [11]-[17], lattice gas models [19]-[21], social force models [22]-[26], and so on. These models are summarized in Table 1.

The exit choice of evacuation for pedestrians in large venues with multiple exits is a significant problem to study. Lo *et al.* [8] proposed a non-cooperative game theory based exit choice model. Fu *et al.* [9] improved the least effort algorithm and considered crowd density around the exits to simulate the exit selection process in the evacuation. Ehtamo *et al.* [10] proposed an exit selection model based on the game-theoretic concept of best response dynamics, where each pedestrian updated the strategy periodically according to the strategies of others.

Evolution algorithms have also been applied in evacuation modeling. In [27], [28], the authors proposed to use improved artificial bee colony for the path planning and exit selection of pedestrians to reduce the evacuation time. Goto *et al.* [29] proposed to utilize ant colony optimization in wide-area complex evacuation scenario considering the danger zones when natural disasters happen. However, these papers assumed that the pedestrians are highly familiar with the environment and rational enough to identify the optimal path, which may not be the case in reality, especially when pedestrians are not familiar with the surrounding environment.

Pedestrian evacuation in large enclosed public spaces like museums is a tough problem because most pedestrians are in panic and not familiar with the environment. In this situation, pedestrians tend to herd and follow others. Therefore, in this paper, an evacuation model called Dual-Strategy Adaptive Particle Swarm Optimization (DSAPSO), which

TABLE 1: COMPARISON OF RESEARCHES IN DIFFERENT FIELDS

Model Based	Design Objective	Reference	Proposed Solution
Physical feature analysis	Physical design for evacuation safety	[1], [2]	Provide a risk-based method to build fire safety design
Network flow	Evacuation planning	[3]	Provide a nonlinear traffic flow network model which is coupled to gaseous hazard information
	Better predictions for evacuation times	[4]	Present a macroscopic and microscopic model using a bidirectional coupling method
Agent-based	Calculation on passenger evacuation performances from Metro Stations	[5]	M/G/c/c models and a multiagent-based simulation approach
	Investigate the specific influence of spatial change	[6]	Consider more factors about the knowledge of evacuees
Game theory	Deal with moving conflicts involving two or three pedestrians	[7]	Consider selfish and selfless behaviors in evacuation
	Exit selection	[8]	Use non-cooperative game theory to deal with individual interaction
	Exit selection	[9]	Improve the least effort algorithm and consider crowd density around the exits
	Exit selection	[10]	Introduce the best response dynamics scheme in exit selection
Cellular automaton	Fasten the calculation speed and consider crucial human behaviors	[11]	Quantify evacuation process with three fundamental forces
	Model collective effects and self-organization phenomenon	[12]	Propose a two-dimensional cellular automaton model
	Improve the security performance and providing better estimates	[13]	Consider the probability of changing route and group fields
	Improve simulation accuracy	[14]	Consider the non-local interaction between pedestrians
	Evaluate the average pedestrian flow through an exit	[15]	Consider the behavior of pedestrians close to the exit
	Simulate the evacuation in a classroom	[16]	Take the occupant density around exits into consideration
	Demonstrate the herding behaviour during evacuation	[17]	Utilize particle swarm optimization algorithm to simulate group behavioursp
	Simulate evacuation in a room with serval exits	[18]	Propose a two-dimensional model considering spatial distance and occupant density
Lattice gas	Simulate the evacuation process in a smoky room	[19]	Take into account the empirically observed behavior
	Simulate the evacuation process in public buildings	[20]	Incorporate the lattice gas model and the social force model.
	More accurate simulation of evacuation process	[21]	Take the population density into consideration
Social force model	Mimic the dynamic behaviors of the pedestrians	[22]	Use dynamical features in the evacuation
	Improve the efficiency of pedestrian evacuation	[23], [24], [25]	Evaluate the dynamic behaviors of guided pedestrians
	Demonstrate the phenomenon of herding	[26]	Utilize ants to simulate the process

is based on particle swarm optimization (PSO) and cellular automaton (CA) is proposed, with the individual features and behaviors are taken into consideration. Moreover, to simulate the spontaneous gathering process in evacuation, we use affinity propagation clustering (APC) to divide people into heterogeneous groups as the swarms of the PSO, which can better match the reality.

PSO [30] originates from the herding behavior in nature, considering the cognition of both individuals and society to pursue the collective goal, which is well suited for the emergency evacuation. Many variants of PSO have been developed over the last decades, for example, cooperative co-evolving PSO [31] designed for high-dimensional problems and orthogonal PSO [32] used previous information more efficiently. PSO is a classical optimization algorithm in evolutionary computation, which has been applied in many areas. Mana *el al.* [33] proposed schedules of workflow in cloud computing with improved PSO. Jeong *el al.* [34] utilize PSO to solve the combinatorial problems in power systems. During the optimization process in PSO, each particle searches the optimal solution based on the cognition of both itself and society. Compared with other optimization algorithms, this kind of cognitive behavior is a good fit for crowd modeling. The position of each particle is updated based on the velocity, which can be controlled and observed easily. Moreover, the best particle in the swarm exerts its one-way influence on all the other particles, which can be considered as the leader [35]. There are a number of applications of PSO used in evacuation, which mainly focus on evacuation routing optimization with PSO [36], [37]. However, few applications of PSO simulates social and individual behavior in evacuation. In [17], a modified particle swarm optimization based human behavior model has been proposed. And Tsai *el al.* [38] proposed a PSO-based simulation framework to simulate in a simple way. However, these works did not consider the features of pedestrians and assumed the velocity unchanged and global best individual varies with time, which is not consistent with the reality.

Cellular Automata (CA) is used to describe the movement of pedestrians in the proposed DSAPSO model. The existing researches show that CA quantifies the evacuation venue with discrete cells [11]. It was initially proposed to simulate pedestrian dynamics by Schadschneider *et al.* [12], who considered as an efficient way to mimic the behavior of people. It belongs to grid-based models, which perform the movement of pedestrians by a discrete process. In recent years, CA is used in many studies about pedestrian behaviors on evacuations. Pereira *et al.* [13] proposed a CA-based model considering route changes and distance of pedestrians in a group, allowing the pedestrians to change their directions and move to the exit together. In order to avoid collision during the evacuation process, Uma *et al.* [14] studied the anticipation influence in pedestrian dynamics. Furthermore, Yanagisawa *et al.* [15] analyzed the suitable position of the exits and the outflow of exits. Some researches focus on the dynamics of a certain area, for example, Liu *et al.* [16] proposed a modified CA model to study the density near the exits.

The abovementioned studies mainly focus on individual behavior, like competition with people nearby [7], exit selection [8], direction control [13], and obstacle avoidance [16]. However, the behaviors of pedestrians on evacuation include not only the individual behaviors but also the social behaviors, such as the leader impact. Pedestrians tend to huddle when the emergency happens in the real-world, especially in large enclosed spaces such as stadiums, museums, and libraries, where they are not familiar with the buildings and the people around them. On one hand, pedestrians that belong to the same group like family members, tourist groups are more likely to leave together, which forms evacuation groups. On the other, the trained staff in these places will guide the people nearby to evacuate, which forms other groups. Visitors who are alone and not familiar with buildings also tend to follow other groups. Yang *et al.* [23] proposed the guides are necessary and of value in the evacuation process. There are many works related to guidance in the evacuation process. Hou *et al.* [24] stressed the significance of leaders in the emergency scheme, particularly in large enclosed spaces. Yang *et al.* [25] proposed a modified social force model for guided crowd evacuation. In these models, guides are mostly related to trained staff members. However, visitors who are familiar with the environment can also play the role of leaders in pedestrian emergency evacuation. Therefore, the proposed DSAPSO model uses APC for population partition and improved PSO algorithm for evacuation strategy generation, to simulate the evacuation of pedestrians in an emergency at large venues with multiple exits. Moreover, we take the individual and social features into consideration on the movement simulation using CA. The proposed models can provide supports for layout optimization of exits and management of pedestrian evacuation at large venues.

The novelties of this model are listed below

1) Combines the concept of APC and PSO with CA models to simulate pedestrian emergency evacuation. The concept of APC is used for population partition, and the improved PSO algorithm and CA model are used to simulate the social and individual behavior in evacuation.
2) Considers the individual difference. We consider the imparity of pedestrians such as age, mobility ability, environmental familiarity, and psychological quality in CA models to simulate the evacuation of pedestrians at large venues. Compare to the traditional CA models, in which the individuals are mostly considered identical with uniform velocity and moving behaviors, the proposed model considers more social and individual behaviors.
3) Utilizes a novel partition method APC to simulate the clustering process of pedestrians into groups in emergency evacuation. The proposed method does not require a predefined number for the clusters, which simulates the clustering process more naturally and precisely.
4) Develops dual-strategy and Adaptive PSO in updating

the leaders and the other pedestrians. In view of the differences between leaders and the other pedestrians, we update positions in a dual-strategy way. The leaders can recognize the best way out, while the other individuals are not familiar with the environment and may move following the surrounding pedestrians and with the experience of his/her own. Hence, leaders play a vital role in the evacuation process. Moreover, an adaptive PSO model is proposed to tackle the situation changes during the evacuation process.

The rest of the paper is organized as follows. In Section II, we introduce the whole process of the proposed DSAPSO algorithm and the details of its components. In Section III, DSAPSO is adopted in a CA-based scenario, and we derive the main features and behaviors to be considered. Numerical results are presented in Section IV and the conclusion is drawn in Section V, respectively.

II. DSAPSO DESIGN

A. MODEL FRAMEWORK

The modeling process of DSAPSO is illustrated in FIGURE 1. In this model, we first utilize APC to cluster the population (all the pedestrians in the venue) into a number of groups, with each group representing a swarm in PSO. After clustering, each swarm selects the desirable exit and elect the capable leader considering the characteristics of each pedestrian. Each swarm then evolves and updates the positions of the pedestrians with the proposed DSAPSO model until all pedestrians reach the exit. In the DSAPSO model, the leaders and other individuals update their positions with different strategies, which is called dual-strategy (DS), as their individual features are different. To simulate the interaction between pedestrians and the environment, during the evacuation process, the parameters in the proposed model change adaptively as the environment and crowd distribution varies. We define the objective function as the minimization of the distance between the selected exit and the position of each particle. The details of the formulated problem will be shown in Section II-C.

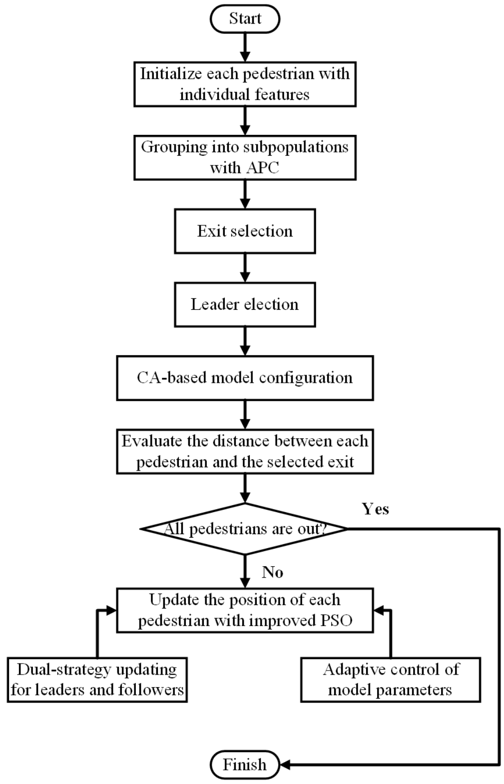


FIGURE 1: The flowchart of DSAPSO.

B. APC BASED SWARM INITIALIZATION

To utilize DSAPSO in an emergency evacuation, the first problem to address is to cluster the pedestrians into a number of non-overlapping groups, which are the swarms in standard PSO.

The traditional clustering methods such as k-means clustering and mean-shift clustering [39], [40], [41] are not the ideal choices to our problem, due to their sensitivity in some predefined parameters, like the number of clusters. The Affinity Propagation Clustering (APC) method, which does not need to predefine the number of clusters, considers all pedestrians as potential exemplars and is demonstrated to yield a satisfactory result in clustering [42].

APC is originally proposed by Frey and Dueck [42]. Instead of randomly electing some exemplars and then iteratively refining them, this method exchanges real-valued messages between individuals to acquire high-quality clusters. Two kinds of messages are exchanged between individuals, responsibility, and availability. The responsibility $r(i,k)$ is sent from individual i to individual k, in which i is the current candidate exemplar, and k is one of the other individuals. It is a reflection of the suitable degree for individual i to serve as the exemplar of individual k. The availability $a(i,k)$ is sent from candidate exemplar k to individual i, which shows the relative appropriate degree for individual i to choose individual k as its exemplar considering the responsibilities from other supporting individuals to the candidate exemplar k. The message-passing process is shown in FIGURE 2.

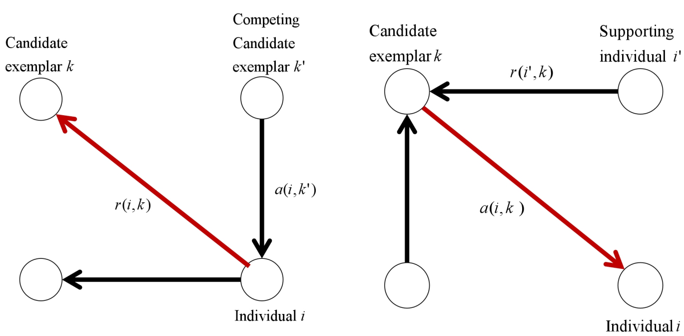


FIGURE 2: Message-passing in APC. Sending responsibilities $r(i,k)$ and availabilities $a(i,k)$ between the individuals.

APC takes similarity $s(i,k)$ between individual i and k as the input, which is computed by using the negative squared error (Eu-clidean distance): $s(i,k) = -\|x_i - x_k\|^2$, and x_i is the location vector of individual i. In each iteration, the responsibilities and availabilities are updated using the following rules

$$r(i,k) = s(i,k) - \max_{\forall k', s.t. k' \neq k} \{r(i,k') + s(i,k')\} \tag{1}$$

$$a(i,k) = \begin{cases} \min\{0, r(k,k) + \sum_{i' \notin \{i,k\}} \max\{0, r(i',k)\}\} & \text{i} \neq k \\ \sum_{i' \neq k} \max\{0, r(r',k)\} & \text{i} = k \end{cases} \tag{2}$$

Where k' is one of the other individuals except $k' = k$. To avoid numerical oscillations and utilize the previous messages, the value of the last iteration is taken into account. Therefore, during the message-passing procedure, each message is set to λ times of its value from the last iteration plus $(1-\lambda)$ times of its current value computed in (1) and (2).

$$r(i,k) = \lambda \times r(i,k)_{last} + (1-\lambda) \times r(i,k) \tag{3}$$

$$a(i,k) = \lambda \times a(i,k)_{last} + (1-\lambda) \times a(i,k) \tag{4}$$

The iteration process may terminate after a predefined number of iterations $mits$, or when the clustering result stays constant for a fixed number of iterations $cits$. To preserve more messages from previous iterations, the parameter λ is set as a relatively large number 0.9, which yields more stable clustering results and reducing numerical oscillations. Moreover, in our evacuation model, the parameters $mits$ and $cits$ are set as 150 and 25 [42] respectively, as it can preserve the accuracy of the results and alleviate the computational burden at the meantime.

In order to partition all the individuals into swarms to implement DSAPSO, the size of each swarm is set in the range of $[4, 50]$ to prevent oversize or undersize of each swarm. If the size of one swarm is too large, one more APC will be performed within the swarm to satisfy the limitation of swarm size. If the size of swarm is too small, it will be merged with surrounding swarms.

C. PSO BASED OPTIMIZATION MODEL

Particle Swarm Optimization (PSO) is a stochastic global optimization technique used to find the optimal region of complex search space. Based on the research about the feeding behavior of flocks of birds and groups of fish, PSO is initially proposed by Kennedy and Eberhart [30]. Imagine a scenario where a bird flies around in a search space toward its goal, it adjusts its position according to its own experience and the experience of its surrounding companions. By learning both social and individual behaviors, the bird tends to move towards the most promising position. Essentially, PSO is an evolutionary computation algorithm by simulating biological behavior in nature.

In PSO, the swarm comprises of a group of particles, and each particle is associated with two vectors, the velocity vector $V_i = [v_i^1, v_i^1, \cdots, v_i^D]$ and the position vector $X_i = [x_i^1, x_i^1, \cdots, x_i^D]$, where D stands for the dimensions of the solution space. The fitness of each particle is determined by the optimization function, and X_i is the position of the particle, indicating a potential solution. In this problem, the optimization function can be the distance from the particle to the exit. Record the best solution of each swarm that minimizes the optimization function of each particle $pBest = [pBest_1, pBest_2, \cdots, pBest_N]$, and N is the number of particles in the swarm. Simultaneously, we record the best solution of the whole swarm $gBest$. And each particle can update their position based on the experience of its history $pBest_i$ and the global best $gBest$. The evolutionary process performs in an iterative way until the iteration number reaches I, and during each iteration, the velocity and position are updated using the following rules

$$\begin{aligned} v_i^d =& \omega \times v_i^d + c_1 \times rand_1^d \times (pBest_i^d - x_i^d) \\ & c_2 \times rand_1^d \times (gBest_i^d - x_i^d) \end{aligned} \tag{5}$$

$$x_i^d = x_i^d + v_i^d \tag{6}$$

where d is the current dimension, ω is the inertia weight [43], c_1 and c_2 are acceleration coefficients, and $rand_1^d$ and $rand_2^d$ are random numbers generated independently within [0, 1]. The updating rules indicate that the velocity of particle i is composed of three parts: the memory of its historic velocity, the impact of its best position in history, and the global best position. In these parameters, ω can influence the convergence, where a relatively small ω has a good performance in local searching and improves solution accuracy, while a larger ω is more capable of global searching. c_1 reflects the effect of the optimal position of individual memory on speed during the flight , which is the individual cognitive coefficient. c_2 reflects the effect of the overall optimal position of the whole group on the speed, which is the social learning factor. In practice, these parameters are essential to gain satisfying performance. The pseudocode is shown in algorithm 1, which is composed of two parts, initialization, and updating. In this algorithm, itr is the current iteration number.

In the evacuation model, V_i and X_i are two-dimensional vectors, in which each dimension represents the x direction and y direction in a 2D environment. We use $fit(X_i)$ to describe the fitness of particle i, which can be defined as the distance between the particle and the selected exits

$$fit(x_i^1, x_i^2) \tag{7}$$

where (x_1, x_2) is the location of the particle in a 2D environment. This function is determined by the specific evacuation scenarios. The optimal value is 0 when the particle reaches the selected exit. In this model, each pedestrian is considered as a particle in the swarm. As we aim to evacuate all the pedestrians out of the venue, we can define the objective function of pedestrian i as follows

$$\begin{aligned} \min \quad & fit(x_i^1, x_i^2) \\ \text{s.t.} \quad & \\ & x_i^1 \in [0, M], \\ & x_i^2 \in [0, N], \\ & v_i \in [v_{min}, v_{max}]. \end{aligned} \tag{8}$$

where M is the length of the venue, N is the width of the venue, v_{min} and v_{max} are the minimum and maximum value of the velocity. Note that these constraints are elementary, the movement of each particle is under the rules detailed in the following sections.

Algorithm 1 PSO Algorithm

```
procedure INITIALIZATION
    for i = 1 to N do
        Initialize velocity V_i and position X_i for particle i
        Evaluate particle i
        Set pBest_i = X_i
    end for
    set gBest=min {pBest_1, pBset_2, ···, pBest_N}
    set itr = 0
end procedure
procedure UPDATING
    while itr < I do
        for i = 1 to N do
            Update the velocity and position of particle i
            Evaluate particle i
            if fit(X_i) < fit(pBest_i) then
                pBset_i = X_i
            end if
            if fit(pBest_i) < fit(gBest) then
                gBest = pBest_i
            end if
        end for
        itr = itr + 1
    end while
end procedure
```

D. DUAL-STRATEGY UPDATING RULES

In this model, each pedestrian is considered as a particle in the swarm, and the collective goal is to approach exits. In standard PSO, the leader (global best), is designated as the best individual in the swarm, which indicates that the leader may alternate during the evolution process. However, empirically the leader would remain unchanging under normal circumstances, based on the following two assumptions

1) In large enclosed spaces like museums and stadiums, most pedestrians are not familiar with the environment, which means they only have a vague impression on the location of the exits. As a consequence, pedestrians in each swarm tend to follow the leader or other people.
2) The leaders, as we can see in the Section III-D, are either selected in each swarm or designated as professional workers who are more qualified and familiar with this area, surely possess high overall qualities. Herein, instead of following others, they are more likely to head straight to the desirable exits in proximity at a relatively high speed.

To address this problem, we propose dual-strategy updating rules for the leaders and other pedestrians. For the leaders in the swarms, they play a predominant role that guides the other pedestrians to the exits. The behaviors of surrounding pedestrians will have little impact on them, which demonstrates that they will automatically seek the best routes. For other pedestrians, they are inclined to panic and follow the leaders.

- *Strategy 1-Update to the best available location if the current pedestrian is a leader:* The leader will update his/her location, but in a way differs from the traditional standard PSO. In each time slot, the leader will select the possible location in the next time step that is nearest to the exit. If the selected place is not available, for example, it is already occupied by another individual, the alternative selection becomes the suboptimal location. This selection-verification process will repeat until the leader finds the desirable choices or all the better locations are occupied, and if there are not any better locations available, he/she will stay at the current location until the next time step.
- *Strategy 2-Update using the rules in PSO if the current pedestrian is not a leader:* As a pedestrian in evacuation, his/her mobile behaviors are dominated by social recognition and individual recognition. Herein, the velocity of the pedestrian will be updated using (4). Moreover, if a pedestrian comes close enough to the exits, i.e. the distance between pedestrian i and the desirable exit is closer than a certain small value c, it is not necessary for him/her to follow others as this pedestrian can clearly see the exit. Under this circumstance, the pedestrian will update using strategy 1. In our model, c is set as 2 meters.

E. ADAPTIVE CONTROL OF PARAMETERS

As shown in Section II-C, the parameter inertia weight ω is of vital importance in the evolution of PSO. It denotes how much a pedestrian will follow the velocity of his/her last iteration. A relatively large ω is more capable of searching globally, whereas a smaller ω performs better in local searching, so normally the parameter ω gradually decreases with iteration to gain a satisfying performance. In reality, the reaction of people may change when they are getting closer to the exits, thus they tend to converge and search around the neighborhood. However, the evacuation process is complex, so the traditional method which linearly decreases with iterations is not the optimal scheme, as it neglects the interaction between the environment and pedestrians. To

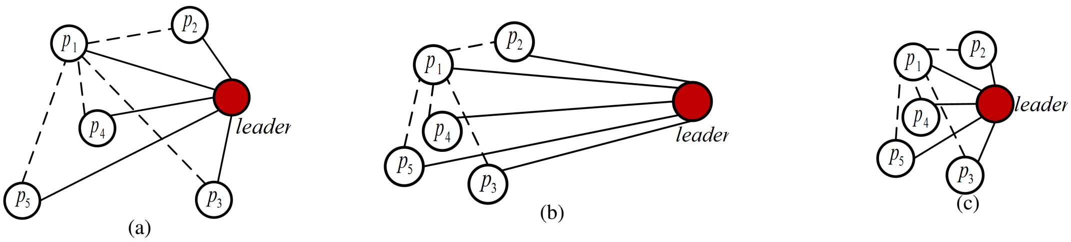


FIGURE 3: The distribution information during the evacuation process, where the real line denotes the relationship between the leader and all the other pedestrians, the dotted line denotes the relationship between different pedestrians, in which we only draw the relationship between $p1$ and all the other individuals for better illustration. a) The individuals exploring with a relatively mutual distance. b) The leader walks foremost and guides others. c) Other individuals follow the leader and converge.

control the PSO evacuation process, this section derives an adaptive control approach based on the swarm distribution information.

1) Swarm Distribution Information in PSO

During the PSO process, the population distribution characteristics vary as the evolution goes on and on. For example, if the leader is surrounded by pedestrians in proximity, the pedestrians can easily recognize the leader and pursue their collective goals. However, if the leader is far from other pedestrians in the swarm and the population distribution is dispersive, the increased social distance may lead to decreased social recognition, as shown in FIGURE 3. The real line denotes the relationship between the leader and all the other pedestrians, while the dotted line denotes the relationship between different pedestrians, in which we only draw the relationship between $p1$ and all the other individuals for better illustration. When a swarm of pedestrians searches and updates their velocities and positions based on the experience of the leader and the experience of themselves, it is reasonable to expect that the distribution information has a great influence on the overall behavior of the swarm. The population distribution information and evolutionary state were introduced in [44], here we extend this method and utilize it in DSAPSO.

The distribution information in FIGURE 3 can be formulated by computing the mean distance of each pedestrian to all the other pedestrians, as illustrated in [45]. Hence, the population distribution information will be calculated in each generation in the following rules.

1) Compute the mean distance of each pedestrian i to all other pedestrians that belong to the same swarm as pedestrian i. Moreover, the distance between pedestrian i and j is measured with Euclidian metric

$$d_i = \frac{1}{N-1} \sum_{j=1, j\neq i}^{N} \sqrt{\sum_{k=1}^{D} (x_i^k - x_j^k)^2} \tag{9}$$

2) Denote the mean distance of the leader as d_g. Compare each pedestrian of the swarm and find the minimum mean distance d_{min} and the maximum mean distance d_{max}. Then we can calculate the evolutionary factor τ, which indicates the population distribution information.

$$\tau = \frac{d_g - d_{min}}{d_{max} - d_{min}} \tag{10}$$

2) Adaptation of the Inertia Weight

The inertia weight ω plays an indispensable role in balancing the global and local search capabilities. Researches have shown the inertia weight should be higher in the beginning and lower as the evolution process converges [30], [46]. It is also comprehensive in this model, as pedestrian i gradually reaches the exits, the velocity in the last generation will have a decreasing impact on his/her current velocity. Hence, with evolutionary factor τ which represents the current distribution information, we can allow τ to control the inertia weight [47].

$$\omega(\tau) = \frac{1}{1 + 1.5e^{-2.6\tau}} \in [0.4, 0.9] \tag{11}$$

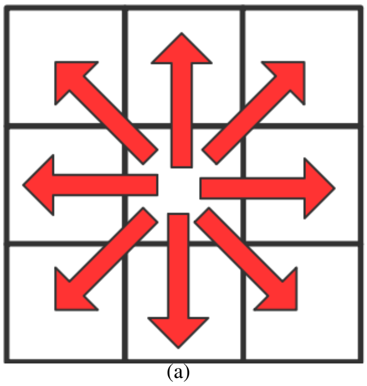
In the evolution process, the swarm will gradually converge, leading to a decrease in τ, as a consequence, the inertia weight ω will gradually decrease, which is able to control the inertia weight adaptively with respect to different distribution information.

III. EVACUATION BEHAVIORS AND FEATURES WITH CELLULAR AUTOMATON

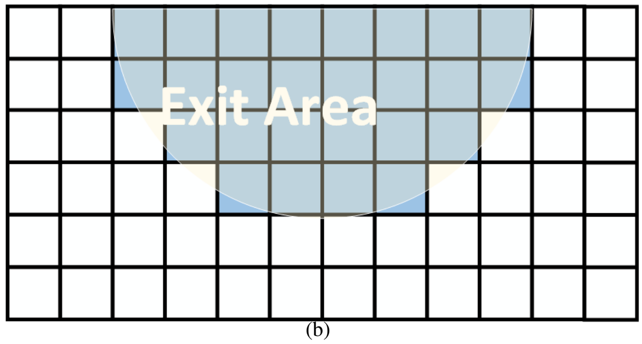
In this model, we apply the proposed DSAPSO method with cellular automaton(CA) in a discrete manner. And the proposed model mainly focuses on simulating the evacuation behavior in a large enclosed public space where multiple exits co-exist. At the same time, we consider some features that influence evacuation behaviors, including the exit selection of each swarm, the mental and physical conditions of each individual, the distribution information of each swarm, and the characteristics of each swarm. In this section, we will discuss these factors and analyze the effects of these factors.

A. BASIC RULES AND ASSUMPTIONS

During the evacuation process, the reactions of different people are unpredictable. Since this model is simulated in a large enclosed public venue with multiple exits, we derive the



(a)



(b)

FIGURE 4: The initialization of the space. (a) Divide the space into a number of cells and the next position a leader may move to and he can also stay in the same cell.(b)The exit area near the exits.

following basic rules and assumptions based on the existing research results [18].

1) Rational effect

When an emergency occurs, pedestrians are all rational and always want to move closer to the exits.

2) Group effect

The whole population is divided into a number of swarms, and a pedestrian will follow the majority of the swarm he/she belongs to in exit selection and moving trend.

3) Inertial effect

Pedestrians are all inertial creatures and they tend to stick to what they are doing. They tend to insist on the same destination once they choose a certain exit and head for it.

B. ENVIRONMENT SETTINGS

The DSAPSO model is based on the traditional CA model [12]. In this paper, the room is modeled as a two-dimensional grid, where each cell can either be occupied by a pedestrian or empty. To cover the average size of the human body, each cell is designed as 0.4m×0.4m based on the researches of other CA models [11]. In the beginning, pedestrians are randomly distributed in the available area without overlapping. During each iteration, each pedestrian will update his/her position to the neighboring eight possible cells or stay at the current cell, as shown in FIGURE 4(a). During the evacuation process, the exit area is an area around the exit, as shown in FIGURE 4(b). It is an essential area in evacuation and congestion may constantly happen here, which is set as a semicircle with a radius of 1.5m, and will be analyzed in Section IV-E.

C. INDIVIDUAL FEATURES

In reality, the mental and physical conditions of each pedestrian are not identical in the evacuation process, and these conditions are crucial in determining what the pedestrians would react in different situations. For example, older people may move at a relatively low speed, and those who have low psychological ability may react hastily. Herein, each pedestrian i is characterized with age, mobility ability, familiarity with the environment and psychological quality, denoted as a_i, m_i, f_i and u_i. In the beginning, these parameters are all randomly initialized in the range of [0,1], which is positively related to these factors.

With these condition of each pedestrian, we can determine pedestrian i's potential to be a leader as q_i

$$q_i = \theta_1 \cdot a_i + \theta_2 \cdot m_i + \theta_3 \cdot u_i + \theta_4 \cdot f_i \in [0, 1] \tag{12}$$

These parameters are determined by the specific evacuation scenarios, which will be discussed in the experimental settings.

D. LEADER ELECTION

After applying the APC method to the entire population, all the pedestrians are partitioned into swarms. The selection of leaders in the process is based on q_i of each pedestrian. Moreover, the number of leaders in each swarm may be more than one due to the fact that there may exist multiple pedestrians with equally high q_i. Moreover, q_i of a leader may decrease in the evacuation process, so it would be better to have another leader to alternate. Hence, we analyze the data and propose a thresh-hold based selection procedure. The threshold value of γ is set as 0.75, where most swarms can select one or two leaders. For those swarms whose best pedestrian i can not satisfy $q_i > \gamma$, we will select the most qualified individual as their leader. Multiple leaders of some swarms indicate that other pedestrians will select the best leader in the qualified leaders of their present swarm as the global best.

E. EXITS CHOICE

This model aims at solving multi-exits evacuation problem, therefore each swarm has to select an appropriate exit as its goal. The collective goal should be the nearest for the whole swarm, so we use the average Euclidian distance between the individual and the exit as the selection standard

$$D = \frac{1}{N-1}\sum_{i=1}^{N}(f(x_i^1, x_i^2) \tag{13}$$

where x_i^1 and x_i^2 denote the position of pedestrian i. For the current swarm, we compute the average distance D from each exit and find the exit j that minimizes the distance. The selected exit is set as the goal of the swarm throughout the evacuation process.

F. SWARM INFORMATION

During the evacuation process, the feature of the whole swarm is also an important factor in influencing the behaviors of pedestrians. For example, a swarm of young people can surely react faster than a swarm of older people. Observing this phenomenon in practice, the feature of swarm j is taken into account, defined as s_j

$$s_j = \frac{1}{N_j}\sum_{k=1}^{N_j} q_{jk} \in [0,1] \tag{14}$$

where N_j denotes the size of swarm j, and q_{jk} denotes the potential of pedestrian k to be a leader in swarm j. The parameter s_j represents the feature of the current swarm, which can be used in the evacuation process in Section III-G to describe the influence of swarm in the movements of pedestrians.

G. INDIVIDUAL BEHAVIOUR

The updating rules for the leaders and the other pedestrians have been illustrated in Section II-D. In the traditional CA model, the velocity is set uniformly in the beginning, ignoring the individual differences. To compensate for the inadequacy of this moving mechanism, we propose a probability-based updating technique, taking into account the pedestrian feature, swarm feature, and surrounding environment during each time slot. Besides, the velocity calculated in the D-SAPSO model will also be considered, both the magnitude and the direction. In other words, during each iteration, the velocity computed in (6) will be primarily used to detect the orientation of the current individual, whereas whether to update the position is determined by a couple of relevant factors. The direction of the pedestrian i is detected by the rules in algorithm 2.

Algorithm 2 Direction Control

```
if |v_i^x| > |v_i^y| then
    if v_i^x > 0 then
        Move in the positive direction of x axis
    else if v_i^x < 0 then
        Move in the negative direction of x axis
    end if
else if |v_i^x| < |v_i^y| then
    if v_i^y > 0 then
        Move in the positive direction of y
    else if v_i^y < 0 then
        Move in the negative direction of y
    end if
else
    Choose a random direction
end if
```

In algorithm 2, the direction of pedestrian i is determined by the numerical value of his velocities in x axis and y axis. After updating the velocities, he/she tend to move toward the direction whose velocity is relatively large. This method is consistent with our experience, as a larger velocity in one direction indicates an inclination to move in this way.

After the calculation of the direction, the location where the individual will move to is decided. However, the individual will not necessarily move in this time slot due to the surroundings and his own mental and physical condition. This means the velocity of each pedestrian varies and cannot be arbitrarily uniformly defined, ignoring the individual difference. Hence, we propose a probability-based mobility control to determine whether the individual would move in each time slot. The determination process follows the following rules

1) Calculate the number of pedestrian n_i in the surrounding 24 cells, which forms a 5×5 square. The parameter congestion d_i is set as $d_i = \frac{n_i}{25}$.
2) Utilize the velocity updated in the PSO procedure, and calculate the velocity factor $e_i = \frac{\sqrt{v_x^2+v_y^2}}{v_m}$, where v_m is the upper bound of the velocity.
2) Compute the possibility factor

$$p_i = \xi + \xi_1(1-d_i) + \xi_2 q_i + \xi_3 e_i + \xi_4 s_i \in [0,1] \tag{15}$$

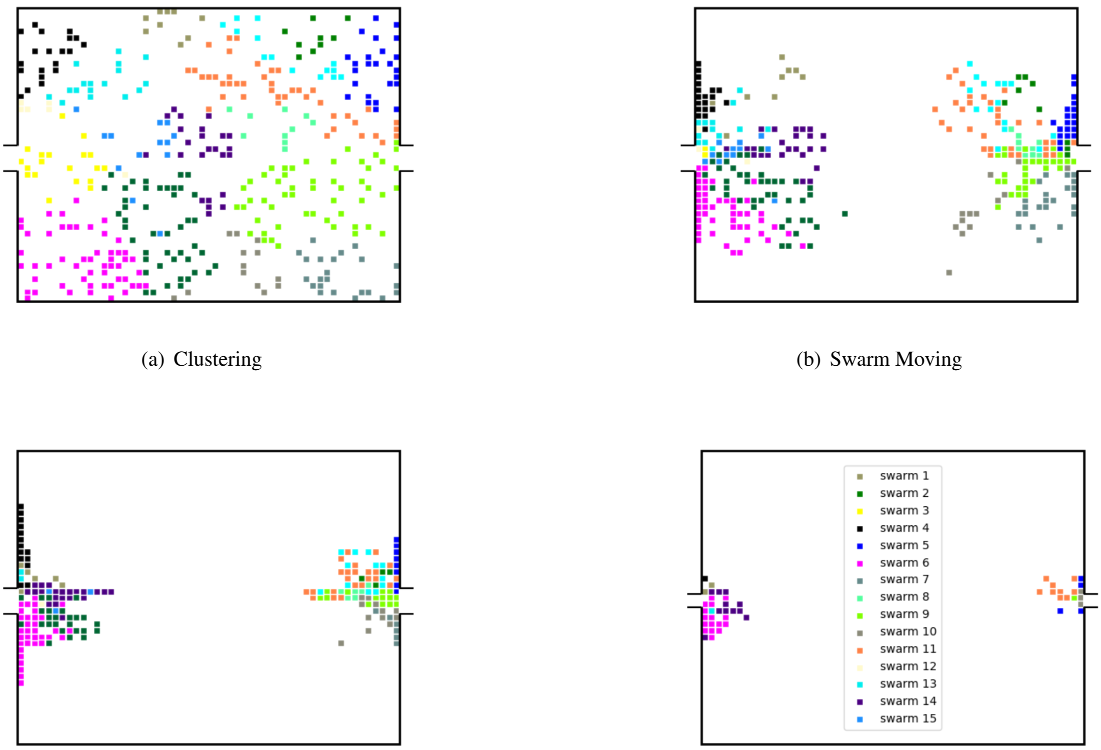
where q_i is the potential to be a leader and s_i is the feature of the swarm that individual i belongs to, which are computed in (12) and (14). The determination of these weights can be set according to the needs of simulation, or according to the actual situation of the simulation environment, therefore these parameters are acquired through Delphi Method by surveys in specific evacuation scenarios.

3) Generate a random number $r \in [0,1]$, update the position of individual i only if $p_i > r$.

From the updating rules above, the moving possibility of pedestrian i is affected by the potential to be a leader, the congestion degree nearby, the current velocity, and the feature of the swarm. Moreover, the base possibility ξ can guarantee every pedestrian has a relatively large possibility to update his/her position in most cases. In the possibility-control process, the determination of each pedestrian is heterogeneous based on the current situation.

IV. SIMULATION AND RESULTS

The DSAPSO model is simulated in different scenarios. As our model is mainly used for large enclosed public space, we take the following two scenarios (a) two exits in a 22m×18m venue with 400 pedestrians to evacuate. (b) two



(a) Clustering

(b) Swarm Moving

(c) Arching

(d) Ending

FIGURE 5: The population distribution during the evacuation process. a)In the initialization, the pedestrians are clustered into a number of swarms. b)Each swarm heads for its own goal. c)Arching at the exits when most pedestrians are near the exits. d)The evacuation process comes to an end.

exits in a 30m×15m venue with 450 pedestrians to evacuate. Moreover, the exits are initially located on both sides of the room, but later, their locations and quantities are changed to analyze the differences in the results. In the beginning, the width of the door is 1.2m, and we also do experiments with a variety of door sizes to see the impact of door width. Finally, we compare our model with some traditional models, like the social force model and cellular automaton with forces essentials(CAFE) model. The simulation runs 30 times for each scenario to acquire authentic data. According to [48], some traditional phenomenons in human evacuation like arching, clogging, and herding, etc are analyzed to validate the performance of the proposed evacuation model, and the comparison with some traditional models indicates it is promising and consistent to the reality.

A. ACQUIRE THE MODEL PARAMETERS AND OBJECTIVE FUNCTIONS

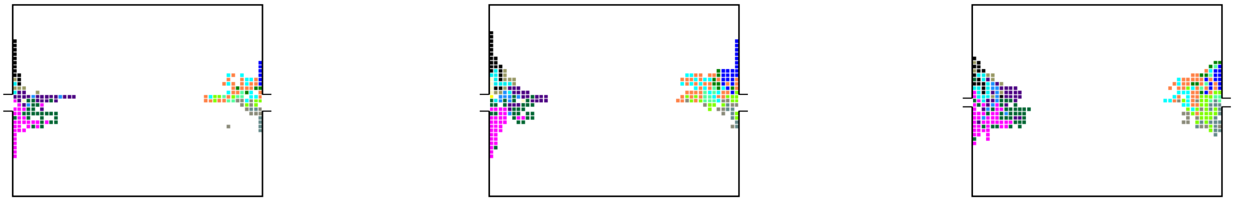
The parameters in this model are the weights of different factors in (12) and (15). These parameters are generally dependent on the evacuation environment, as in different situations we care about different factors of pedestrians. For example, in large public space where many pedestrians are not familiar with the environment, familiarity with the environment can be considered to be dominant, while in other situations we may reconsider its importance. Therefore, we adopt Delphi Method to acquire these parameters of this evacuation scenario and finally set them as $\theta_1 = 0.1, \theta_2 = 0.2, \theta_3 = 0.1, \theta_4 = 0.6, \xi = 0.4, \xi_1 = 0.2, \xi_2 = 0.2, \xi_3 = 0.1, \xi_4 = 0.1$. In Section IV-G, we will discuss the impact of different value range of the factors. Besides, our experiments are set in simple scenarios without obstacles, hence we can set the objective function $f(x_i^1, x_i^2)$ as

$$fit(x_i^1, x_i^2) = |x_i^1 - \hat{y}_1| + |x_i^2 - \hat{y}_2| \tag{16}$$

where $(\hat{y}_1, \hat{y}_2)$ is the position of the selected exit for particle i.

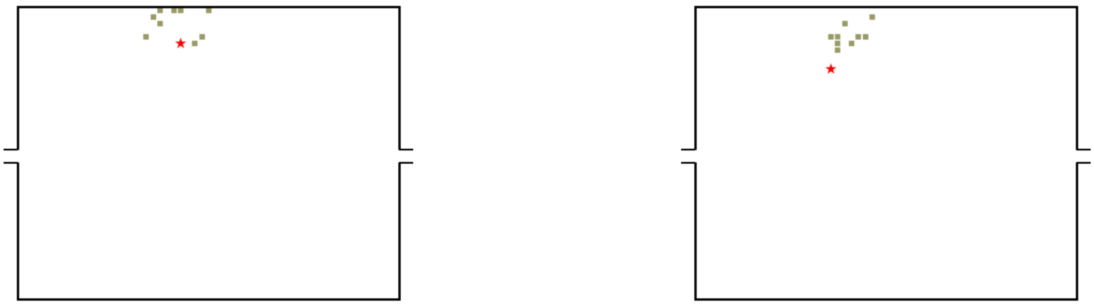
B. THE WHOLE PROCESS OF EVACUATION

There are mainly four states during the evacuation process in the proposed model, as shown in FIGURE 5. The experiments are conducted in scenario (a). In the beginning, people are randomly distributed in the space, and those with common interests would cluster into the same swarm. For example, those who are in the same tourist group, or related to each other like friends or family, etc. Other factors can



(a) door width 1.6m (b) door width 1.2m (c) door width 0.8m

FIGURE 6: The arching behavior with different door width at the same time.



(a) leader selection (b) guiding

FIGURE 7: Leader movement

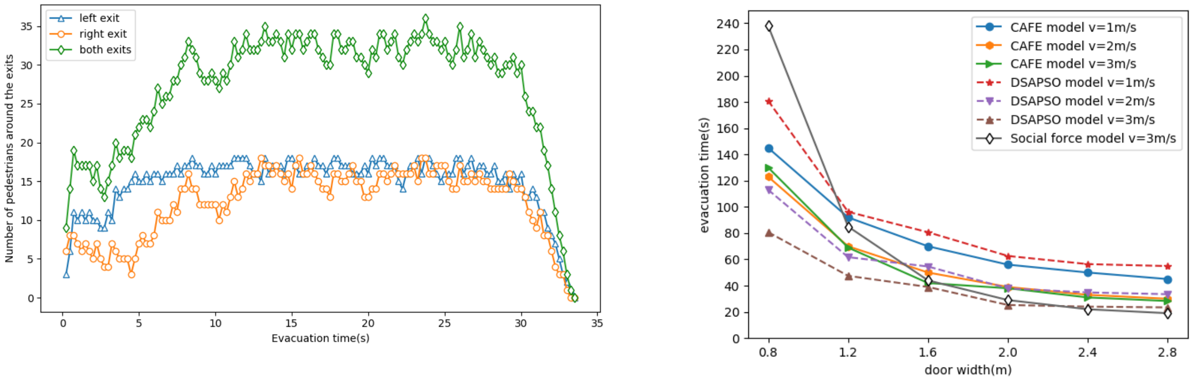
also lead to clustering, like a trained staff nearby would help people to evacuate, as shown in FIGURE 5(a). Different colors denote different swarms or the various groups that herd automatically. As we can see, the APC method clusters the whole population into multiple groups, the size of which ranges from two to forty. The result shows that it performs well in the spontaneous gathering of pedestrians. Then, each swarm would move under the rules of DSAPSO, updating the position with both the cognition of the leader and his/her own. In this way, each pedestrian comes closer to the exits, shown in FIGURE 5(b). Whereafter, the pedestrians around the exits will shape like an arch as exits get increasingly crowded, which is considered as the queuing behavior, as illustrated in FIGURE 5(c). In reality, the arching behavior is a notable feature during evacuation. After the clogging in the exits and most individuals are out, the evacuation comes to an end, as shown in FIGURE 5(d).

C. ARCHING

Arching is a distinctive feature when pedestrians are clogging near the exits. In this experiment, we set the door width as 0.8m,1.2m, and 1.6m respectively in scenario (a) to gauge the difference of the shape, as shown in FIGURE 6. The arching information is acquired at the same time during the evacuation. We can evidently discover that as the door width increases, the arching shape becomes plumper. This phenomenon is common in the evacuation process, and it indicates that the door width is a bottleneck in the evacuation process, determining the queuing behavior as more and more pedestrians getting closer to the door. This experimental result is consistent with those from classical models such as [11], illustrating that the DSAPSO model has some notable features as other widely recognized models and is in line with reality. Moreover, the clogging may promote the panic degree among people, which may lead to a stampede or other accidents. In this situation, the evacuation efficiency decreases and the safety of the people are not ensured. Therefore, by gauging the shape of the arch at the rush hour, it can help the designer to set the optimal door width to reduce the risk of accidents like a stampede.

D. LEADER MOVEMENT

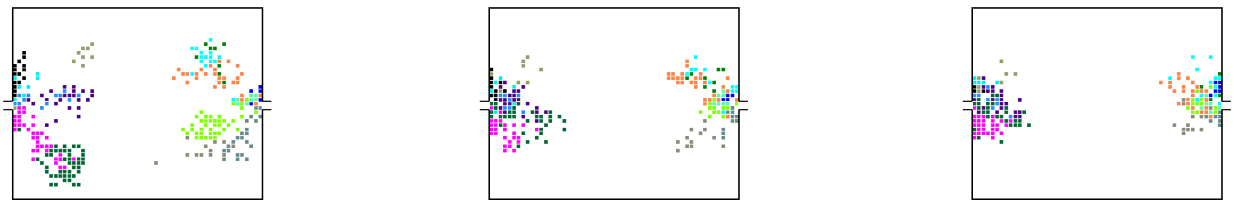
During the evacuation process, the leader, as the global best of a swarm, is essential for the other pedestrians who follow him/her. We simulate in scenario (a) and select a swarm to observe the behavior. As we can see in FIGURE 10, the leader is a pedestrian marked with a pentagram, which is selected in the beginning by the evaluation of q_i. As the leader is relatively more familiar with the environment than any other pedestrians in the swarm, he/she will adopt the best available location while the other pedestrians will explore based on both the leader and his/her own experience.



(a) Number of pedestrians near the exits over time

(b) The effects of different velocity compared with the CAFE model and social force model

FIGURE 8: (a) Analysis of people around the exit area. (b) Comparison with other models.



(a) Not familiar with the environment

(b) A little bit familiar with the environment

(c) Familiar with this environment

FIGURE 9: The behavior of pedestrians with different familiarity range at the same time.

Hence, the leader can update his location more rationally, becoming the fastest to reach the selected exit. As shown in FIGURE 7(b), after a number of iterations, the leader goes first and the other pedestrians will move under the guidance of the leader. When the pedestrians are far away from the leader, the leader impact may decrease as they can hardly recognize the leader.

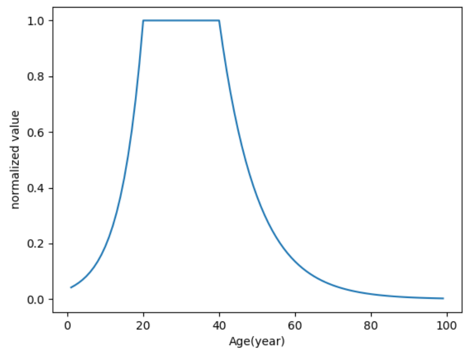
E. CONGESTION AROUND THE EXITS

The congestion around the exits is also analyzed to discover the evacuation process in different exits. Here we take scenario (a) as an example to analyze this process, in which the average speed is 2.0m/s. As shown in FIGURE 8(a), the number of pedestrians around the left and right exits is generally the same. In the beginning, the density rises sharply and then stays at a relatively high value for a long time, which indicates the clogging begins to take shape and the exits are surrounded by the pedestrians. When the evacuation process comes to an end, the density drops to zero in a short time. However, the situation in the two exits is slightly different during the evacuation, especially in the first fifteen minutes. The number of people in the right exit rises and drops for a moment mainly due to the characteristics of swarm movement, as the swarm tends to cluster and move together. After the APC process, there are more swarms of small size near the right exit. At the same time, in the beginning, most pedestrians heading for the right exit have not arrived near the exit, so the swarms of small size near the right exit can reach its destination quickly.

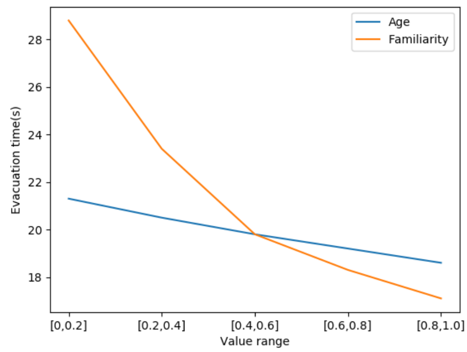
F. ALGORITHM COMPARISON WITH EFFECTS OF DIFFERENT DOOR SIZES AND VELOCITIES

The door size is a bottleneck in the evacuation process, and different velocities can lead to varied results as well. Here we discuss the influence of various door sizes and velocities and compare our model with some widely recognized models in scenario (a).

The social force model is one of the most classic evacuation models [22] which considers the physical and psychological forces and introduces the self-organization behaviors to make the evacuation model more consistent with reality. CAFE model [11] is also a widely accepted evacuation model based on CA. It is an improved cellular automaton model, which describes the evacuation process with three basic forces, namely repulsion, friction, and attraction. We compare our DSAPSO model with the above-mentioned models by evacuation time in different door sizes and velocities, as shown in FIGURE 8(b). The graph shows that our model is comparable to these models at various velocities and door width. As the average velocity increases,



(a) Normalize age into values between 0 and 1



(b) The impact of different value ranges in total evacuation time

FIGURE 10: Impact of factor ranges in determining the potential to be a leader q_i

the evacuation time of the DSAPSO model decreases faster than the CAFE model. Moreover, the proposed model has a better performance compared with the social force model when the door is narrow. The experiments also demonstrate that the door width has a great influence on the evacuation time in an inverse-relative way. When the door width is small, the evacuation time is high and a slight increase in the door width can lead to a big drop in the time. However, as the door width increases, the marginal benefits become less significant, and the evacuation time stays at a relatively small value even when the door width continues to increase. This indicates that the doors do not have to be very wide, as the marginal benefit is low when the door size is over 2m in this simulation scenario. In reality, the door width is not built wide enough in many cases due to the limitation of other factors like the requirements of construction and budget constraints. The experiment can be utilized to determine the optimal choice of door width to make a trade-off between the evacuation efficiency and cost. In FIGURE 8(b), it suggests that the door width of 2m or 2.4m can be a good choice in this simulation scenario, yielding a satisfactory result.

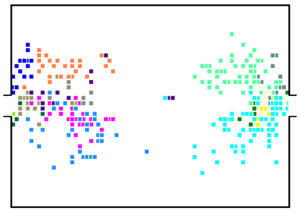
G. EFFECTS OF THE FACTORS DETERMINING THE POTENTIAL TO BE A LEADER

The factors that determining q_i of each pedestrian include age, mobility ability, psychological quality, and familiarity with the environment, as suggested in (12). Different range of these parameters denotes the characteristics of these pedestrians. For example, different range of age values represents the age profile of the swarms, like swarms of young students or middle-aged adults. To gauge the impact of these parameters, we take familiarity as an example, as shown in FIGURE 9, where we increase the familiarity range to gauge the difference at the same time in evacuation. When the pedestrians are not familiar with the environment, as shown in FIGURE 9(a), the distribution of pedestrians is dispersive and disordered, as their individual recognition is feeble and they may search randomly in the neighborhood. As the familiarity increases, as shown in FIGURE 9(b) and FIGURE 9(c), the crowd distribution is more concentrated because the individual recognition is high and they are able to find their way more efficiently. For other factors like age, we can normalize its value into [0,1] with simple conversion function like exponential function, as shown in FIGURE 10(a). By varying the generation of the factors' value within the different range, as shown in FIGURE 10(b), it can be seen that a higher value range can result in shorter evacuation time. Moreover, the familiarity has a greater influence in evacuation time, as we set the weight of familiarity higher in Section IV-A.

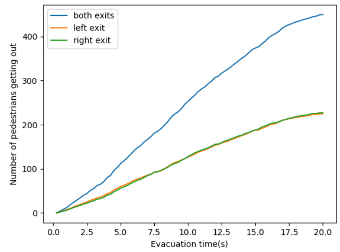
H. EFFECTS OF DIFFERENT LOCATION AND QUANTITY OF EXITS

The location and number of exits play a significant role in the evacuation process. Here we set each door width as 2m and run for 30 times in each case in scenario (b). As shown in FIGURE 11, we rearrange the exits to I)Two exits are located on the left and right side respectively, which corresponds to FIGURE 11(a) and FIGURE 11(b). II)both in the left side of the venue, which corresponds to FIGURE 11(c) and FIGURE 11(d). III)one exit on the left side and the other one at the bottom, which corresponds to FIGURE 11(e) and FIGURE 11(f). IV)two exits on the left side and the third one on the right side, which corresponds to FIGURE 11(g) and FIGURE 11(h). V)two exits on the left side and two exits on the right side, which corresponds to FIGURE 11(i) and FIGURE 11(j), and show the number of people escaping out of each exit respectively. Moreover, all these figures of pedestrian distribution are in the stage of swarm moving of evacuation.

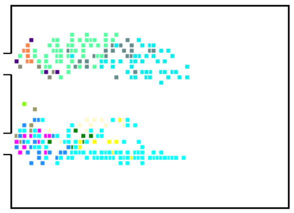
In cases I and II, the two exits are uniformly distributed and symmetrical with different locations, hence the flow of pedestrians are alike, where the slight difference is mainly due to the clustering of swarms. However, the evacuation time in case II is relatively long as people on the right side have to go across the whole venue. This indicates that a higher degree of symmetry in exits' location is able to reduce the evacuation time, as the evacuation time of case I largely exceeds case II. In case III, the exit at the bottom is on the



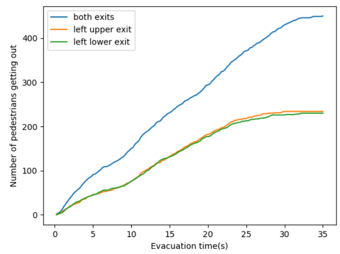
(a) Two exits in the left and right side of the venue respectively



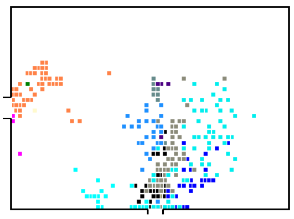
(b) Number of pedestrians getting out in different exits



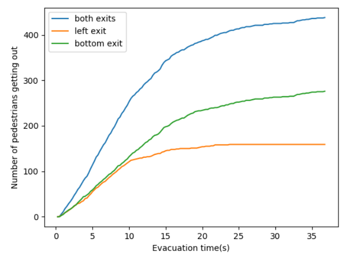
(c) Two exits in the left side of the venue



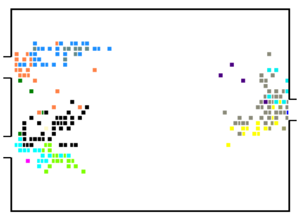
(d) Number of pedestrians getting out in different exits



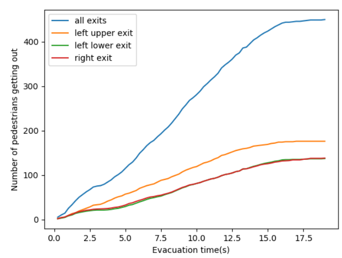
(e) Two exits in the left side and bottom of the venue



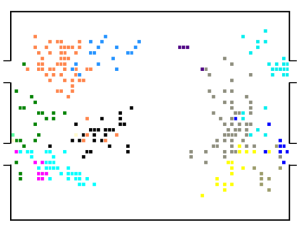
(f) Number of pedestrians getting out in different exits



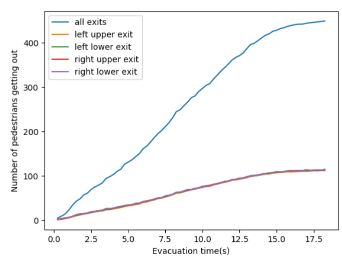
(g) Three exits with two in the left side and one in the right side



(h) Number of pedestrians getting out in different exits



(i) Four exits with two in the left side and two in the right side



(j) Number of pedestrians getting out in different exits

FIGURE 11: The effects of different location and quantity of exits.

long side, hence it is closer to more pedestrians than the exit in the left side, which indicates the human traffic is higher at the bottom. This may lead to clogging, as we can see in FIGURE 11(e), crowd pressure at the bottom is much higher. In this case, more traffic pressure gives way to the bottom exit, thus the evacuation time does not decrease and is roughly equal to the time in case II. In case IV and V, more exits can further help to improve the evacuation efficiency. Observing from the above scenarios, the location of exits is a bottleneck during evacuation and evenly distributed exits are more conducive to evacuation efficiency. In addition, the increase in the number of exits can significantly improve the evacuation efficiency.

V. CONCLUSION AND DISCUSSION

In the evacuation process, the movement of pedestrians is affected by many factors. Due to the limitations of their visibility range and herding behaviors, the movement of the surrounding people plays an essential role. At the same time, the behavior of recognition and familiarity affects the whole process. To capture these behavioral effects, this paper proposed a DSAPSO model utilizing the PSO algorithm to balance the effects of social and individual recognition, which can better simulate the movement of pedestrians in venues where most pedestrians are not familiar with the environment, such as museums, libraries, and stadiums under the guidance of leaders and the experience of their own. APC method is used to divide the whole population into a number of swarms and select the leaders with the best quality. To simulate the dynamic changes of pedestrians, we develop a modified PSO with dual-strategy adaptive control method. Moreover, instead of assuming homogeneous behaviors, this model explicitly takes into account various characteristics of people. The simulation results present the distinctive features of the model like arching, leadership effect, velocity in the evacuation process, and the influence of different door sizes and locations. It is also shown that the performance of our proposed model is promising compared with the CAFE model and social force model when the door width is small and can simulate the evacuation considering the individual characteristics, and is consistent with the reality in some widely-recognized phenomenons, such arching and congestion. The experimental results indicate that the leader has a predominant influence during the evacuation process to guide other individuals. As the door width increases, the decrease in evacuation time is becoming less distinctive, and the optimal choice of door width in the simulation scenario of this paper is around 2m. Moreover, the location and quantity of exits are also important in evacuation, where a higher degree of symmetry in exits distribution helps to evacuate more efficiently.

We have obtained some promising results, however, there are many investigations and modifications that should be done further. In this paper, we only consider a simple configuration of the evacuation environment without obstacles, simulations have not been done on some complex buildings. Besides, more factors could be considered in the movement of the individual, such as the panic degree of the crowd, the clash between pedestrians, the capacity of the door, exit selection, and adaptive leaders when the location of doors are different, these are the factors we need to consider in our future work.

VI. ACKNOWLEDGEMENTS

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