Collective Dynamics

Optimising Pedestrian Flow Around Large Stadiums

Yuming Dong[1] · Xiaolu Jia[2] · Daichi Yanagisawa[2,1,3] · Katsuhiro Nishinari[2,1,3]

[1] Department of Aeronautics and Astronautics, School of Engineering, The University of Tokyo, Tokyo, Japan,
E-mail: dong-yuming@g.ecc.u-tokyo.ac.jp
[2] Research Center for Advanced Science and Technology, The University of Tokyo, Tokyo, Japan
[3] Mobility Innovation Collaborative Research Organization, The University of Tokyo, Chiba, Japan

Received: 27 July 2021 / Last revision received: 6 October 2021 / Accepted: 2 November 2021
DOI: 10.17815/CD.2021.117

Abstract This study proposes a method that combines the cellular automaton model and the differential evolution algorithm for optimising pedestrian flow around large stadiums. A miniature version of a large stadium and its surrounding areas is constructed via the cellular automaton model. Special mechanisms are applied to influence the behaviour of an agent that leaves from a certain stadium gate. The agent may be attracted to a nearby business facility and/or guided to uncongested areas. The differential evolution algorithm is then used to determine the optimal probabilities of the influencing agents for each stadium gate. The main goal is to reduce the evacuation time, and other goals such as reducing the costs for the influencing agents' behaviours and the individual evacuation time are also considered. We found that, although they worked differently in different scenarios, the attraction and guidance of agents significantly reduced the evacuation time. The optimal evacuation time was achieved with moderate attraction to the business facilities and strong guidance to the detouring route. The results demonstrate that the proposed method can provide a goal-dependent, exit-specific strategy that is otherwise hard to acquire for optimising pedestrian flow.

Keywords Cellular automaton · differential evolution · pedestrian simulation · optimisation · evacuation

1 Introduction

Numerous studies have been conducted on the evacuation process during emergency and non-emergency situations. Two aspects are of particular importance: the evacuation time [1] and human behaviour [2]. Recently, human behaviours and the psychology behind them are receiving increasing attention. There are three types of human behaviours that need to be considered: interactions among people, interactions between people and buildings, and interactions between people and the environment [3]. The phenomena generated from these behaviours may not be easily acquired from a real evacuation due to practical limits; therefore, simulation models are necessary to obtain a better understanding of this issue.

Evacuating a large stadium, or a large indoor building space in general, can be extremely lengthy, especially during major events. Many long and complex evacuation routes exist simultaneously for large buildings, and these routes may be subject to sudden changes due to fire, smoke, and other issues that may occur during an emergency [4]. Visibility may be impaired due to smoke and lighting conditions, although this issue may be mitigated through certain devices like phosphorescent guidance equipment [5, 6]. People may have different knowledge of the area, and some of them may have special roles, e.g. staff members or first responders [7]. Coordination and guidance can be provided through normal, predetermined approaches, as well as smart systems that can respond quickly to the situation [8]. Special electronic systems to analyse pedestrian flow have been successfully applied to stadium cameras, facilitating the dynamic management of congestion [9]. Generally, relying solely on pedestrians' spontaneous behaviours may result in an inefficient or unsafe evacuation. Therefore, it is necessary to conduct pedestrian managements to improve the evacuation process.

On the other hand, many studies have focused on the process of leaving buildings and the people that successfully evacuated the buildings. However, congestion can still happen when people are trying to leave the surrounding area after exiting the building. There are studies about the evacuation process that can occur in a large outdoor space during emergencies [10, 11]. We believe that further research is required to understand the non-emergency evacuation process in an outdoor space and optimizing such an evacuation by influencing people's behaviours.

Individual decision-making processes have been proven to be vital for evacuation, with the exit choice being one of most well-studied options [12–14]. Applying dynamic control strategies to influence pedestrians' decisions has now been considered as a viable choice [15]. This may include providing instructions to pedestrians via various devices [14], as well as more traditional options like using road signs and volunteers. Architectural options like redesigning obstacles layout is also a viable choice under certain conditions [16]. For the time being, however, "forcing" pedestrians to make certain choices is not a realistic way to optimize the evacuation. Therefore, we have decided to focus on non-compulsory methods and result-oriented optimization indexes. For example, if attracting people to a nearby shop can shorten the evacuation time, we may focus on the appropriate number of people we need to attract, instead of the exact methods. To simulate these phenomena, we chose to use the cellular automaton model, a simple yet adaptive tool for pedestrian simulations.

The extended floor field cellular automaton model is a well-tested model for pedestrian simulations [17]. In this model, each pedestrian (agent) moves within a grid to simulate the evacuation process. The movement direction is determined by the strength of the floor field, as shown in Fig. 1. Different types of floor fields may be used to represent the different interactions, including the people's knowledge about the environment, the tendency of following others, certain behaviours like staying away from the wall if possible, and the negative effects of hazards like smoke or gas [17–19]. Assuming that there are two types of floor fields in the area (P, P'), the probability of moving to each cell is determined by the floor field strength.

$$p_i = Nexp(kP_i + k'P_i')exp(k_I), i = 1, 2, 3, 4 \tag{1}$$

where N is the normalisation factor; k and k' are the sensitivity parameters. The normalisation factor will ensure the sum of the four probabilities is 1. k_I is an adjustable value that represents the inertia effect, and it is 0 for the directions that are not the movement direction in the previous time step [17–20]. In order to find the optimal layout or strategy in a given scenario, combining certain simulation models with optimization methods has been proven to be a viable option [16, 21].

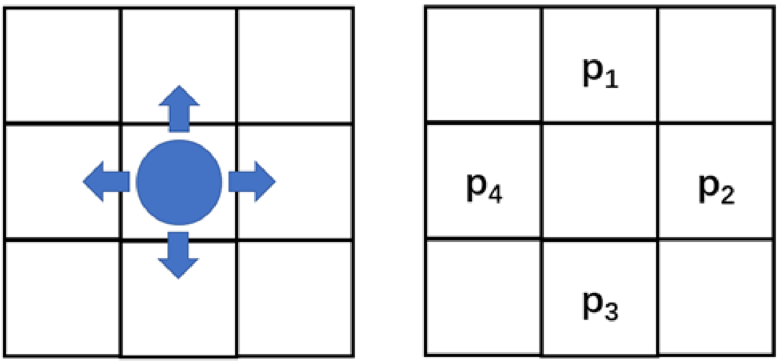

Figure 1 Agent and its target cell (von Neumann neighbourhood) at the next time step.

The aim of this study is to develop a method that is capable of optimising the pedestrian flow around large stadiums. Based on the simulation results that are provided by the cellular automaton model, the program will attempt to optimise the pedestrian flow by influencing people's behaviours with novel mechanisms that we developed. We then introduce a simple and effective optimisation algorithm known as the differential evolution algorithm (DE) to help with this complicated optimisation [22]. Although the size of the simulation is limited due to the sheer number of simulations that are required to run the DE, this method can still provide useful insights about how can we reduce the evacuation time while considering other goals like individual evacuation time and guidance cost.

2 Mini-Dome

We developed an extended floor field cellular automaton model for the area around a large stadium.The cellular automaton model is chosen as a balance between accuracy and computation time. The overall layout that was used as a reference is the Tokyo Dome, a baseball stadium in Japan, and its surrounding area (Tokyo Dome City). Multiple train stations that serve as exits exist in the area, and people may also choose to visit the surrounding business facilities instead of going directly to the train stations after leaving the stadium. Due to the limitation of the computing power,the model is much smaller than the area in reality and is referred to as "Mini-Dome".

2.1 Overview

As shown in Fig. 2, the size of the model is 32 × 55 cells. An aerial view of the area from Google Maps is also given. Each cell represents a 0.4 × 0.4 m square. The north is at the top of the model. Most of the geometry details are missing due to the limited size. Because 2,000,000 simulations are needed per optimisation, it would be extremely time-consuming to run the program if the model becomes excessively large. The blue cells—or the path—are areas that are available for walking. The three train stations in the area (JR Suidobashi, Toei Mitasen Suidobashi, Korakuen) are referred to as stations A, B, and C, respectively. Note that for stations A and C, two separate paths are available. For station A, the path marked by the long orange arrow is referred to as the south path, and the long green arrow marks the southeast path. The business facilities represent the various shops and restaurants within the area.

The 10 × 10 block in the centre represents the stadium. The total number of agents that need to be evacuated is 200. This number is selected because it may provide a long enough time period for us to observe the effect of attraction, guidance, and the congestion of the south path. As shown in Fig. 2, seven gates or stadium exits will continue to generate agents until the total number reaches 200. To avoid confusion, they are referred to as "gates" instead of "exits" in this study. After being generated, the agents will move to the train stations and business facilities to leave the area, and the time it takes to complete this process is defined as the evacuation time. The evacuation process is guided by the static floor field, attraction floor field, and guidance. These three components are covered in the following sections.

2.2 Area Exits: Train Stations and Business Facilities

After being generated at the gates, an agent may leave from a train station or a business facility. The main options for the agents to leave the area involve using the three train stations under the influence of the static floor field. The static floor field is defined as the opposite number of a cell's distance to the train station. In most pedestrian evacuation studies that use the cellular automaton model, an agent can evacuate through any one of the exits that are available. In Mini-Dome, this assumption is not true because different train stations usually offer different train routes. Generally, it is expected that everyone has a train station as the desired destination before leaving the stadium. We can assume that even if one knows that a station may be crowded, using another station is not an option. When an agent is generated, it should be immediately assigned a specific train station as the destination. This destination cannot be changed afterwards.

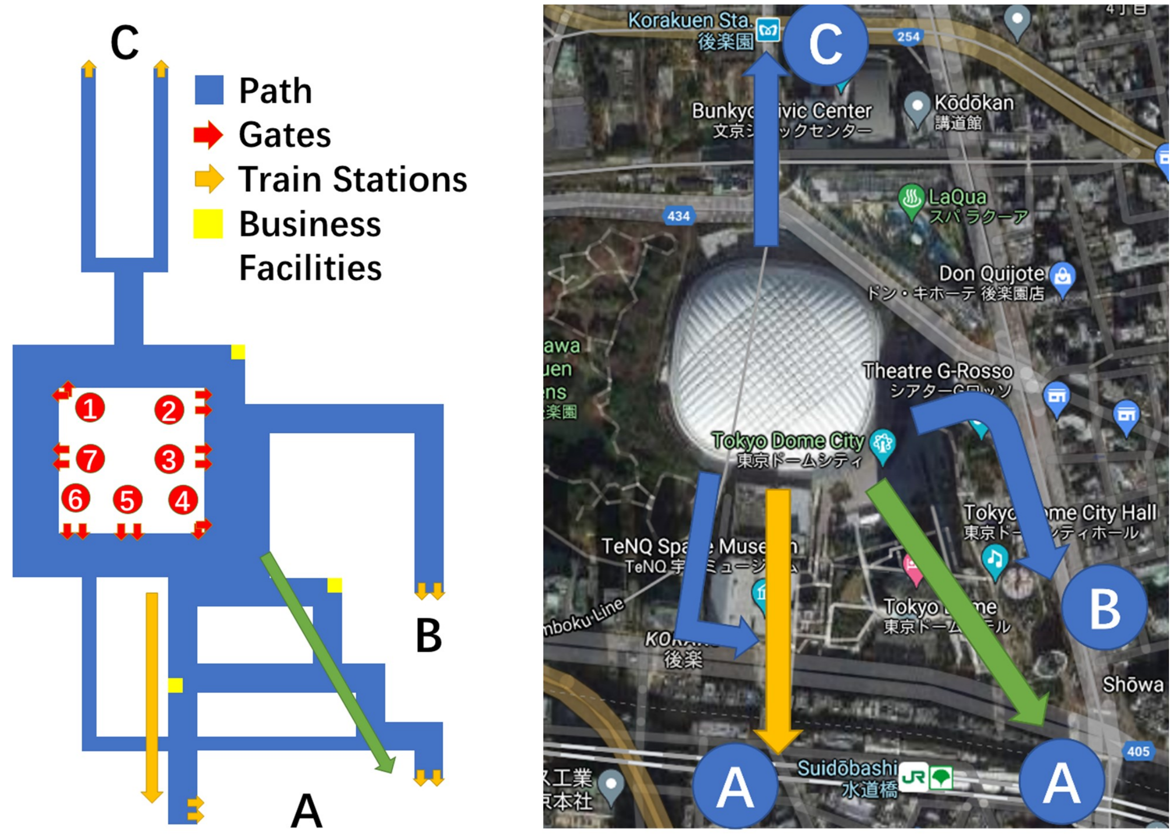

Figure 2 Mini-Dome and aerial view of Tokyo Dome City. Map data: Google Maps, Maxar Technologies, 2021.07.17.

Agents with different destinations will be influenced by different static floor fields, and the areas that are close to each train station are only available for the agents with that train station as the destination. We assume that every agent has full knowledge of the entire area before leaving the stadium. Therefore, the dynamic floor field, which is often used to simulate the tendency of people following others, is no longer needed as every agent knows exactly where to go. Based on our observation, most people enter and leave the Tokyo Dome City through station A, whereas station B and C are not popular choices. Therefore, we assumed that 70% of the agents will choose station A as their destination. For stations B and C, the numbers are 15%.

In reality, the seats in the stadium are often randomly assigned, and people tend to leave the stadium from the nearest exit instead of finding another one. Therefore, we assumed that an agent's destination is not related to the position of the gate that it is generated from.

Finally, we designed the destination selection mechanism as follows: when an agent is generated, regardless of the position of the gate, it has a probability of 70% that it is assigned station A as the destination. The probabilities of being assigned stations B and C are 15%. It is worth noting again that this setting has a distinct feature that seperates Mini-Dome from other models [8, 9, 13–15]: agents' destintaions are randomly determined and cannot be adjusted in order to shorten the evacuationt time. This means that an optimal evacuation strategy will need to consider the random nature of agents' destinations.

In addition to the three train stations that function as the main exits from the area, there are three business facilities that may also function as exits. They represent restaurants, shops, and bars. If an agent chooses to visit a business facility and spend some time in it instead of going directly to the train station, it is likely that the evacuation will have been completed before they leave. Therefore, it is reasonable to say that they are evacuated "through" the business facilities in our simulation. We only considered this type of visit and ignored the ones who only briefly visit the business facilities before leaving. This is because they re-join the crowd in a rather short time, and therefore, cannot be regarded as evacuated.

The key difference between the train stations and business facilities is that each business facility has a maximum capacity of 10, i.e., only a maximum of 15% (30/200) of the agents may evacuate through business facilities. The train stations, however, are assumed to have no capacity limits.

2.3 Attraction

To simulate the process of attracting people to the business facilities with advertisements and other methods, we designed a novel mechanism referred to as "attraction". Usually, pedestrian simulation models assume that agents may only leave the area from the exits on the edge of the model, especially for models about emergency evacuation. For Mini-Dome, this assumption is no longer true, because we are considering an outdoor, non-emergency evacuation with a number of business facilities within the area.

When each agent is generated, it has a probability of becoming "attracted". To achieve a gate-specific strategy, we assume that there are seven independent probabilities, which are referred to as "attraction rates". Theoretically, all the attraction rates can change from 0 to 1. For simplicity, we assume that only the attracted agents can use business facilities to leave the area. The attracted agents may also leave from the train stations, provided that they failed to reach the business facilities or were rejected after a business facility reached its limit.

Attraction rates are result-oriented. In reality, we may influence a certain percentage of people by giving away brochures, launching sales campaigns, as well as other measures. We also hope that this could make our model more versatile, because different stadiums may apply very different method to achieve the same goal.

As an attracted agent approaches a business facility, it will be influenced by the "attraction floor field", an example of which is given in Fig. 3. The attraction floor field will guide attracted agents to the cell where the business facility is located. Unattracted agents will not be influenced by the attraction floor field.

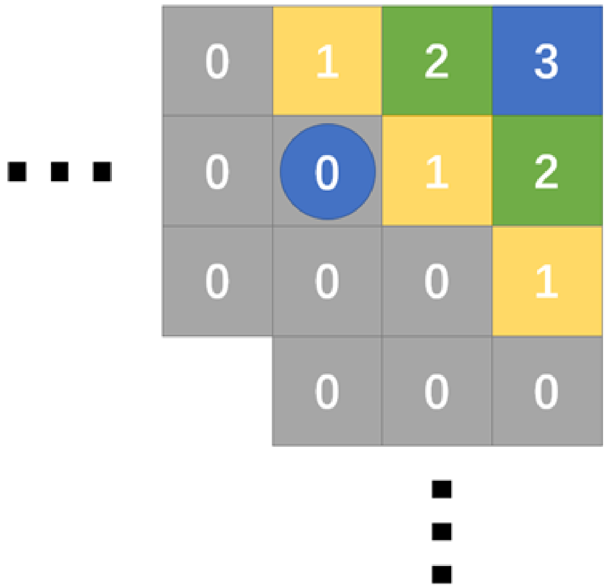

Figure 3 Attraction floor field around a business facility, which is located in the top-right blue cell. An attracted agent (the blue circle) is moving within the area.

Assume that during the last timestep the agent moves to the right to reach the current position. Then, for the attracted agent (the blue circle in Fig. 3), the probabilities of moving to the surrounding cells are as follows:

$$p_i = \begin{cases} Nexp(k_S S_i + k_A A_i)exp(k_I) & (i = 2), \\ Nexp(k_S S_i + k_A A_i) & (i \neq 2), \end{cases} j = 1, 2, ..., D \tag{2}$$

where the sensitivity parameters are $k_S = 3$, $k_A = 1$, and $k_I = 0.2$ in our simulation. The index $i \in 1, 2, 3, 4$ represents the direction as shown in Fig. 1. S and A are the values of the static and attraction floor field, respectively. In the case of Fig. 3, $A_1 = A_2 = 1$ and $A_3 = A_4 = 0$. As mentioned before, the business facilities stop accepting agents once the capacity limit has been reached. However, the attraction floor field will still influence the attracted agents even if the business facility is at full capacity. This will interfere with the normal evacuation process and increase the evacuation time. We believe that this might represent how the pedestrian flow can become hindered if a long queue exists outside of a business facility.

2.4 Guidance

The southeast path to station A (Fig. 2) is seriously underused in the simulation and in real life. This is because this route is much longer than the south path (Fig. 2). Naturally, we may guide agents to this path to reduce the congestion on the south path. This mechanism is referred to as “guidance”. Similar to attraction, an agent also has a probability of

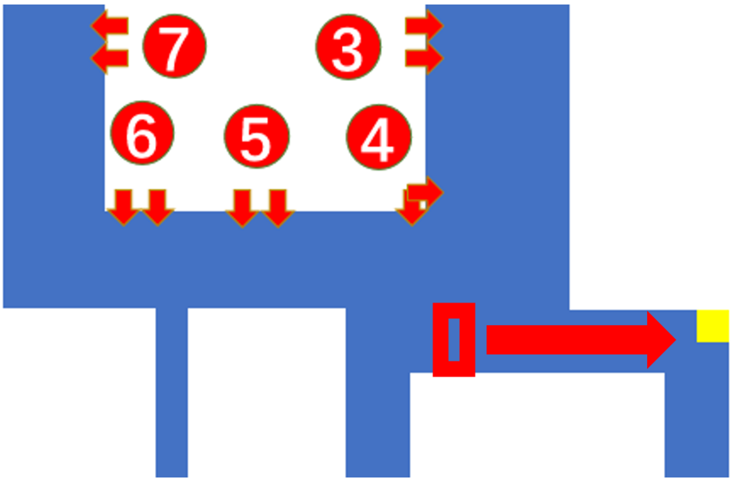

Figure 4 Guidance of the agents to use the southeast path to station A.

becoming "guided" once it is generated. The two processes are independent from each other; therefore, it is possible for an agent to become attracted and guided, or unaffected by both. The guidance rates, which can change from 0 to 1, are assigned to seven gates. The guided agents are forced to enter the southeast path once they have reached the area that is marked by the red box in Fig. 4. Afterwards, they will temporarily ignore all the floor fields and move in the direction of the red arrow.

If they cannot reach these two cells, they may also evacuate normally through the train stations and/or business facilities (if attracted). The longer path requires more time steps for an agent to evacuate. However, because the south path usually sees heavy congestion, the evacuation time will often decrease as the guidance rates increase.

It is worth noting that attraction and guidance cannot change agents' destinations. An agent influenced by attraction may not visit a business facility for certain reasons: it may not reach the place during the evacuation; the business facility is full; it walks away due to sheer possibility. An agent influenced by guidance does not have to use the southeast path, if it manages to evacuate through other paths. We believe this may better simulate the human psychology. For example, if one leaves the stadium with a brochure of a nearby shop in his/her hand, he/she will be more likely to visit the shop if it comes in sight on the way home. However, it is less likely that he/she will be looking for it carefully before going home, resulting in a change in destination or route choice. For simplicity, we only consider the first scenario.

3 Differential Evolution Algorithm

The differential evolution algorithm (DE) is a simple yet powerful evolution algorithm that was proposed by Storn and Price in 1997 [22]. The population-based stochastic technique has been proven to be highly effective when used in multiple fields [22–24]. This section briefly describes how the algorithm works and how it is integrated with the cellular automaton model. Similar to other evolution algorithms, the DE generates a population with N vectors randomly within the D-dimensional search space. Each vector in is a D-dimensional vector, and it is called an individual. In our case, N=10 and D=14 (seven attraction rates and seven guidance rates). The search space range is [0,1]. The value of the ith individual on the jth dimension may be generated as follows:

$$x_i^j = rand[0,1], j = 1,2,...,D. \tag{3}$$

The second step is to calculate the fitness values of all the individuals. The goal of the DE algorithm is to find an individual that has the smallest fitness value possible. The fitness value is usually generated from a specific function. In this study, the fitness value can only be acquired from running the simulations for a certain number of times while setting the values of an individual as the attraction and guidance rates. The determination of the fitness value is covered in section 4. After acquiring the fitness values for all the individuals, a mutation operation is carried out to generate a mutated individual (mutant vector) for each individual (target vector). There are many types of mutation strategies. The strategy we applied is to find three random individuals (except for the individual undergoing the mutation itself): x_{r_1},x_{r_2},and x_{r_3}. The mutated individual V_i can be expressed as follows:

$$V_i = x_{r_1} + F(x_{r_2} - x_{r_3}), \tag{4}$$

where F is the differential weight and F is defined as 0.85.

The next step is crossover. Each pair of the mutant vector and target vector will undergo a crossover operation to generate a new trial vector U_i. For each dimension of the trial vector, we can calculate the value by a simple binomial crossover strategy that is defined as follows:

$$U_i^j = \begin{cases} V_i^j, & if\ rand[0,1] \leq P_{CR}\ or\ j = j_{rand} \\ x_i, & otherwise \end{cases} \quad j = 1,2,...,D, \tag{5}$$

where j_{rand} is a randomly selected dimension and P_{CR} is the crossover probability. j_{rand} will ensure that at least one parameter of the trail vector is from the mutant vector [22]. We can set P_{CR} as 0.5. The crossover operation essentially merges the mutant vector and target vector. The simple mutation and crossover strategies separate DE from genetic algorithms.

Finally, all the individuals will be checked to determine if they have values that exceed the upper and lower bounds. If so, these values will be changed to the upper and lower bounds, or 0 and 1 in our case. The fitness values of all the individuals will be evaluated again. If it has lower or equal values than the fitness value that was acquired last time (meaning U_i is better), U_i will replace x_i. Otherwise, x_i will not change.

The above process will continue until the maximum number of iterations has been reached (here, 100). We selected this small number to keep the computation time within an acceptable range. As discussed above, the fitness value for a single individual needs to be evaluated for twice in one iteration. Therefore, for one optimisation with 10 individuals and 100 iterations, we need to evaluate the fitness values for 2×10×100=20,000 times.

How DE interacts with Mini-Dome is shown in Fig. 5. DE gives Mini-Dome an individual that is comprised of seven attraction rates and seven guidance rates, then Mini-Dome

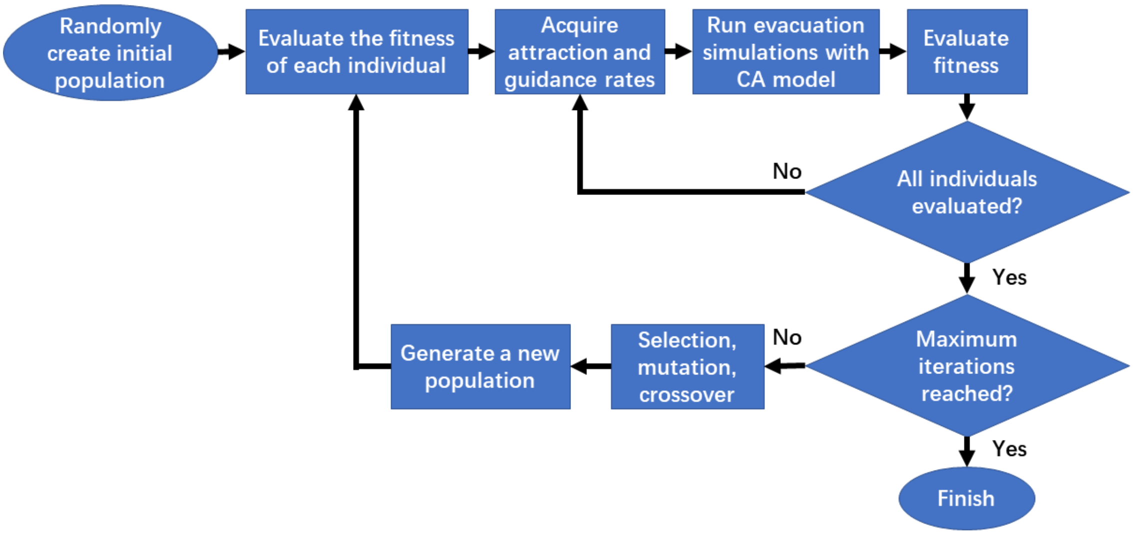

Figure 5 The block diagram of optimization process. An individual is comprised of seven attraction rates and seven guidance rates.

will give DE the fitness of that individual after performing a number of simulations. The two components operate relatively independently.

4 Results and Discussion

4.1 Number of Simulations Needed

Many random elements exist in the Mini-Dome. Therefore, for each set of attraction rates and guidance rates, we need to simulate the Mini-Dome a number of times and calculate the average to obtain stable results. Agents with different destinations will often have conflicts with each other in the central area. This feature largely increases the stochasticity level of the model, influencing the accuracy of evacuation time we acquired.

To determine how many times we need to simulate the Mini-Dome to gain a stable evacuation time, we tested several numbers. The results are given in Tab. 1. Note that the average values and standard deviations are calculated from 200 independent tests, and each test gives the average result from a certain number of simulations. A K-S test was carried out to confirm that the 200 results follow the noraml distrbution. It fails to reject the null hypothesis that it does not come from such a distribution at 1% significance level.The similarity is demonstrated in Fig. 6. Based on the feature of normal distribution, there is a 95% chance that the result falls into range of [219.3790-2*0.8181,219.3790+2*0.8181]. The error should be below 0.75% for 95% of the time. If the number of simulations decreases to 500, the error will become much larger (below 1.1%). Running 2000 simulations for each fitness value is slightly more accurate, however, the computation time will

Number of Simulations	100	300	500	1000	2000
Average Fitness Value	219.2848	219.4513	219.3231	219.3790	219.3696
Standard Deviation of the Fitness Value	2.4465	1.5937	1.2211	0.8181	0.6179

Table 1 Averages and standard deviations of the fitness values when running the simulations for a given number of times.

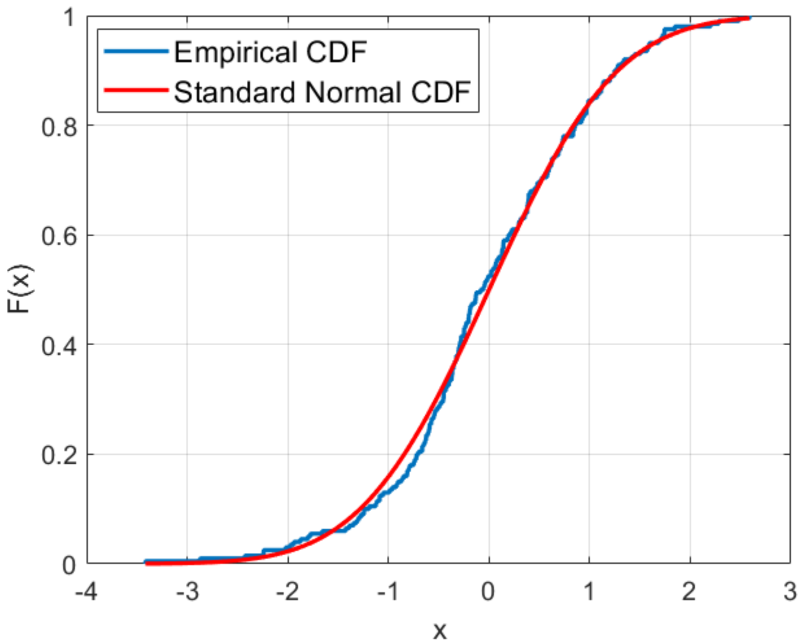

Figure 6 The cumulative distribution function of empirical data (our results) and standard normal distribution

be unacceptable.

We selected 1,000 as a balance between the accuracy and feasibility. For each one of the 10 individuals, its fitness value will have to be checked twice in every iteration. Because we ran the DE for 100 iterations, it was necessary to conduct 2×10×100×1,000=2,000,000 simulations for a single optimisation. This number means that the size of the CA model must be highly limited to complete the 2000000 simulations within reasonable time. The limited size is another major source of error in this study. In addition, the DE itself is a stochastic optimisation method that may generate random errors as well.

4.2 The Effect of the Attraction and Guidance

To demonstrate how the attraction and guidance influence the evacuation time, we may consider a special scenario where every gate uses the same attraction rate and guidance rate. As shown in Fig. 7, the attraction rate will have a negative impact on the evacuation

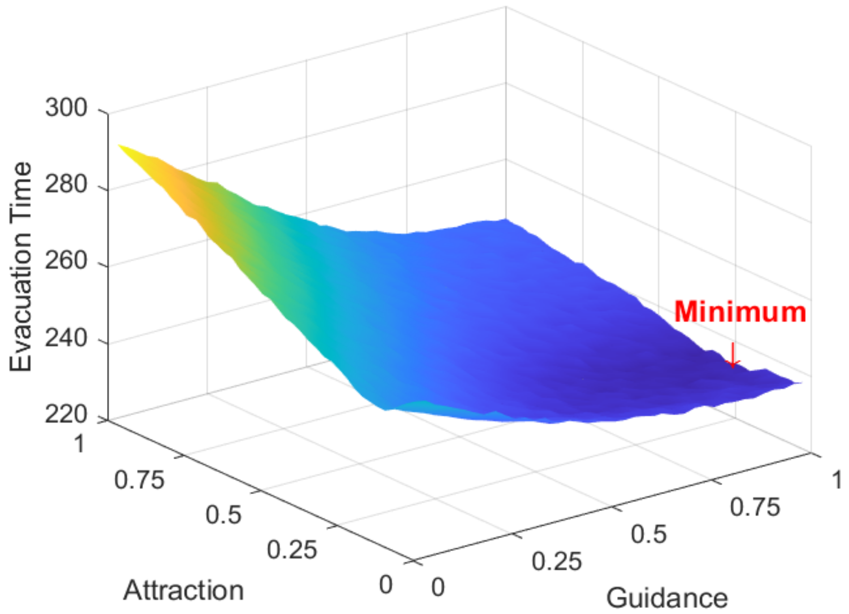

Figure 7 Change in the evacuation time if all the gates use the same attraction and guidance rate.

time once they have reached a certain value. When the guidance rate is 1, the optimal attraction rate is around 0.25. The minimum evacuation time can be achieved this way in this special scenario. For other guidance rates, there is an optimal attraction rate that can minimise the evacuation time. From this result, we may speculate that there are optimal rates that can minimise the evacuation time, and we can use DE to find it.

4.3 Results from the Three Scenarios

To better understand the effect of the attraction and guidance, three scenarios are considered.

1. Basic: The basic scenario disabled the attraction and guidance, so it can be used as a baseline to evaluate the results from the other two scenarios. The result of this scenario is from the average of 100,000 simulations.

2. Ideal: In the ideal scenario, we assumed that the attraction rates and guidance rates can change freely from 0 to 1, and only the evacuation time needs to be optimised. The fitness value is simply defined as

$$Fitness = EvacTime \tag{6}$$

In real life, we cannot expect that advertisements or other methods are capable of attracting 100% of the people to the business facilities. However, it is difficult to imagine that

Scenario	Fitness Value	Evacuation Time	T_{max}	G
Basic	N/A	257.5752	N/A	N/A
Ideal	217.1404	217.1404	70.1982	5.6349
Realistic	307.4740	225.3247	78.7663	3.1264

Table 2 Fitness values, evacuation time, maximum individual evacuation time, and guidance cost results from the three scenarios.

no one will visit the business facilities after leaving the stadium. Therefore, this scenario is referred to as "ideal". Because the DE will only try to optimise the evacuation time, it is possible that several agents will have to stay in the area for a very long time before leaving the area. The results of the ideal scenario are the average for 10 independent optimisations.

3. Realistic: In the realistic scenario, we assumed that there are upper limits and lowers limits for the rates (0.05–0.5), and the DE will also try to optimise the indexes other than the evacuation time. The fitness value is defined as follows.

$$Fitness = EvacTime + T_{max} + G \tag{7}$$

where T_{max} is the maximum individual evacuation time, and G is the sum of the seven guidance rates. Two additional indexes are considered: the maximum individual evacuation time and the guidance cost. The program tracks each agent to know how long it takes for every agent to leave the area. Even if the evacuation time is the same, it is possible that certain agents may require a lot of time to evacuate. For example, if an agent uses the southeast path to go to station A after being generated at gate 1, the process may take more than 70 time steps, whereas most agents may evacuate in 30–50 time steps. The aim is to make this phenomenon happen less often. The guidance cost represents the cost of hiring volunteers, putting up signs, and other necessary actions for guiding the pedestrian flow. Even though the evacuation time is usually much larger than the guidance cost, the former usually changes between 215 and 230 timesteps. This means that a change in the latter will have an impact on the fitness value. The attraction cost is not considered because the people that are attracted to business facilities will also generate profits. For simplicity, we assumed that the two effects cancel each other out. Similar to the ideal scenario, the results are also from the average of 10 independent optimisations. The results are shown in Tab. 2, Tab. 3, Tab. 4, and Tab. 5. An example of the convergence curve is given in Fig. 8.

The most obvious result is that the attraction and guidance significantly reduce the evacuation time. However, the two mechanisms work differently in different scenarios. In the ideal scenario, we may see that gate 1, which is far from the shops, should have the highest attraction rates. For the other gates, attraction is not even required. This means that extra advertisement efforts should be made in gate 1 to attract people and optimise the flow. Because gate 1 is the farthest from station A, it will be beneficial to attract as many agents as possible to business facilities, instead of letting them walk to station A

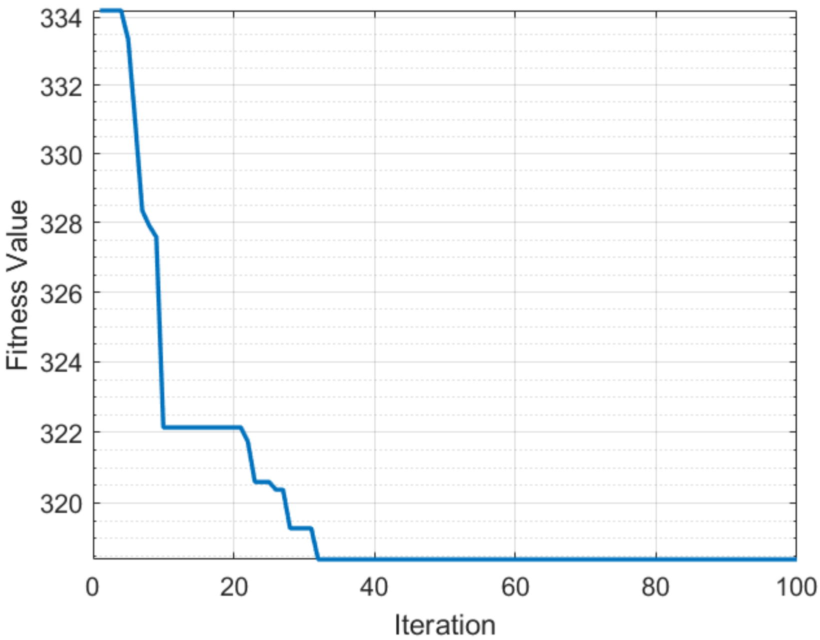

Figure 8 The convergence curve of an optimization. Note that the numbers are different from the data in the tables, which is the average of 10 optimizations.

Scenario	Station A1	Station A2	Station B	Station C	Business Facilities
Basic	133.5547	6.4948	30.0018	29.9488	0
Ideal	82.5025	39.3567	27.1350	29.9064	21.0813
Realistic	100.5963	22.2227	27.6290	29.1465	20.4055

Table 3 The number of agents left from each station and the business facilities. Agents leaving from the south path (A1) and the southeast path (A2) to station A are recorded separately.

Scenario	Gate 1	Gate 2	Gate 3	Gate 4	Gate 5	Gate 6	Gate 7
Ideal	0.8054	0.0173	0.0038	0.0018	0	0.0322	0.0089
Realistic	0.4965	0.2486	0.0584	0.0615	0.0856	0.1208	0.2283

Table 4 Attraction rates for each gate given by the DE. Basic scenario is not included because the attraction is disabled.

Scenario	Gate 1	Gate 2	Gate 3	Gate 4	Gate 5	Gate 6	Gate 7
Ideal	0.9781	0.9265	0.9696	0.9371	0.9270	0.5594	0.3463
Realistic	0.4976	0.4970	0.4989	0.4981	0.4833	0.4075	0.2440

Table 5 Guidance rates for each gate given by the DE. Basic scenario is not included because the guidance is disabled.

and cause the congestion. To avoid the negative effect of the attraction, other exits should have limited advertisements.

In general, higher guidance rates are better, especially for gates 1–5. Therefore, guidance is more important than attraction, provided that everyone can follow orders in terms of where they should go. The organisers should focus on guiding everyone (or everyone using gates 1–5 at least) to use station A through the southeast path, if possible. This conclusion may be interpreted as the strategy for extremely important and stressful occasions like the Olympic games. For these situations, the evacuation time may be the only concern due to safety issues, whereas the budget and manpower are usually not issues.

In the realistic scenario, the attraction is still very important for gate 1, although gate 2 and gate 7 are also seeing higher attraction rates. Gate 2 and gate 7 are close to gate 1, therefore attracting agents generated from these two gates are also more effective than other options. The effectiveness of the guidance is slightly reduced by considering the individual evacuation time and guidance cost, and less agents can be guided to use the southeast path. This is more similar to a stressful yet normal scenario like baseball league matches. Even though the evacuation time is still important, the costs for guiding people cannot be too high. Advertisements and other methods for attraction will have to play a more important role during an evacuation. The efforts for the attraction and guidance should be more carefully distributed among the gates.

5 Conclusion

In this study we developed a method that combines the cellular automaton model and differential evolution algorithm. The method is capable of simulating and optimising the pedestrian flow around a large stadium. Several novel modifications, namely the destination selection, attraction, and guidance, are made to improve the simulation of human behaviours during a non-emergency evacuation. Strategies for different purposes can be given after integrating the model with the differential evolution algorithm. We can also identify which gates are of particular importance, and which gates are not.

However, our model was much smaller than the actual area owing to the limited computing power of our system. In the future, we plan to build a larger, more ideal model to perform additional simulations. By carefully adjusting the layout, the evacuation process may become clearer. The process of attraction of an agent or the guiding mechanism may be adjusted during the evacuation process, instead of being determined during the generation, to better represent what happens in real life.

Acknowledgements This work was supported by JSPS KAKENHI grant numbers JP21H01570, 21H01352, and 21K14377, as well as JST-Mirai Program Grant Number JPMJMI20D1, Japan.

References

[1] Gwynne, S., Galea, E., Owen, M., Lawrence, P.J., Filippidis, L.: A review of the methodologies used in evacuation modelling. Fire and materials **23**(6), 383–388 (1999). doi:cz9k2c

[2] Sime, J.D.: An occupant response shelter escape time (orset) model. Safety science **38**(2), 109–125 (2001). doi:10.1016/S0925-7535(00)00062-X

[3] Yang, L., Zhao, D., Li, J., Fang, T.: Simulation of the kin behavior in building occupant evacuation based on cellular automaton. Building and Environment **40**(3), 411–415 (2005). doi:10.1016/j.buildenv.2004.08.005

[4] Wu, Y., Kang, J., Wang, C.: A crowd route choice evacuation model in large indoor building spaces. Frontiers of architectural research **7**(2), 135–150 (2018). doi:10.1016/j.foar.2018.03.003

[5] Jeon, G.Y., Hong, W.H.: An experimental study on how phosphorescent guidance equipment influences on evacuation in impaired visibility. Journal of loss Prevention in the Process Industries **22**(6), 934–942 (2009). doi:10.1016/j.jlp.2009.08.008

[6] Kobes, M., Helsloot, I., De Vries, B., Post, J.G., Oberijé, N., Groenewegen, K.: Way finding during fire evacuation; an analysis of unannounced fire drills in a hotel at night. Building and Environment **45**(3), 537–548 (2010). doi:10.1016/j.buildenv.2009.07.004

[7] Chu, M.L., Law, K.H.: Incorporating individual behavior, knowledge, and roles in simulating evacuation. Fire technology **55**(2), 437–464 (2019). doi:10.1007/s10694-018-0747-6

[8] Lujak, M., Billhardt, H., Dunkel, J., Fernández, A., Hermoso, R., Ossowski, S.: A distributed architecture for real-time evacuation guidance in large smart buildings. Computer Science and Information Systems **14**(1), 257–282 (2017). doi:10.2298/CSIS161014002L

[9] Tsiftsis, A., Georgoudas, I.G., Sirakoulis, G.C.: Real data evaluation of a crowd supervising system for stadium evacuation and its hardware implementation. IEEE Systems Journal **10**(2), 649–660 (2015). doi:10.1109/JSYST.2014.2370455

[10] Yoo, B., Choi, S.D.: Emergency evacuation plan for hazardous chemicals leakage accidents using gis-based risk analysis techniques in south korea. International journal of environmental research and public health **16**(11), 1948 (2019). doi:10.3390/ijerph16111948

[11] Liu, S., Liu, J., Wei, W.: Simulation of crowd evacuation behaviour in outdoor public places: A model based on shanghai stampede. International Journal of Simulation Modelling **18**(1), 86–99 (2019). doi:10.2507/IJSIMM18(1)464

[12] Crociani, L., Vizzari, G., Yanagisawa, D., Nishinari, K., Bandini, S.: Route choice in pedestrian simulation: Design and evaluation of a model based on empirical observations. Intelligenza Artificiale **10**(2), 163–182 (2016). doi:10.3233/IA-160102

[13] Yu, B.: Consideration of tactical decisions in microscopic pedestrian simulation: Algorithm and experiments. Transportation research part C: emerging technologies **119**, 102742 (2020). doi:10.1016/j.trc.2020.102742

[14] Lopez-Carmona, M.A., Garcia, A.P.: Cellevac: An adaptive guidance system for crowd evacuation through behavioral optimization. Safety science **139**, 105215 (2021). doi:10.1016/j.ssci.2021.105215

[15] Molyneaux, N., Scarinci, R., Bierlaire, M.: Design and analysis of control strategies for pedestrian flows. Transportation **48**(4), 1767–1807 (2021). doi:10.1007/s11116-020-10111-1

[16] Zhao, Y., Li, M., Lu, X., Tian, L., Yu, Z., Huang, K., Wang, Y., Li, T.: Optimal layout design of obstacles for panic evacuation using differential evolution. Physica A: Statistical Mechanics and its Applications **465**, 175–194 (2017). doi:10.1016/j.physa.2016.08.021

[17] Nishinari, K., Kirchner, A., Namazi, A., Schadschneider, A.: Extended floor field ca model for evacuation dynamics. IEICE Transactions on information and systems **87**(3), 726–732 (2004)

[18] Huang, K., Zheng, X., Cheng, Y., Yang, Y.: Behavior-based cellular automaton model for pedestrian dynamics. Applied Mathematics and Computation **292**, 417–424 (2017). doi:10.1016/j.amc.2016.07.002

[19] Zheng, Y., Li, X., Zhu, N., Jia, B., Jiang, R.: Evacuation dynamics with smoking diffusion in three dimension based on an extended floor-field model. Physica A: Statistical Mechanics and its Applications **507**, 414–426 (2018). doi:10.1016/j.physa.2018.05.020

[20] Burstedde, C., Klauck, K., Schadschneider, A., Zittartz, J.: Simulation of pedestrian dynamics using a two-dimensional cellular automaton. Physica A: Statistical Mechanics and its Applications **295**(3-4), 507–525 (2001). doi:10.1016/S0378-4371(01)00141-8

[21] Zhong, J., Luo, L., Cai, W., Lees, M.: Automatic rule identification for agent-based crowd models through gene expression programming. In: Proceedings of the 2014 international conference on Autonomous agents and multi-agent systems, pp. 1125–1132 (2014)

[22] Storn, R., Price, K.: Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces. Journal of global optimization **11**(4), 341–359 (1997). doi:10.1023/A:1008202821328

[23] Ilonen, J., Kamarainen, J.K., Lampinen, J.: Differential evolution training algorithm for feed-forward neural networks. Neural Processing Letters **17**(1), 93–105 (2003). doi:10.1023/A:1022995128597

[24] Zhang, Y., Gong, D.w., Gao, X.z., Tian, T., Sun, X.y.: Binary differential evolution with self-learning for multi-objective feature selection. Information Sciences **507**, 67–85 (2020). doi:10.1016/j.ins.2019.08.040