Crowd Modeling and Simulation for Safer Building Design

Original Scientific Paper

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Abstract *– Crowd modeling and simulation are very important in the investigation and study of the dynamics of a crowd. They can be used not only to understand the behavior of a crowd in different environments, but also in risk assessment of spaces and in designing spaces that are safer for crowds, especially during emergency evacuations. This paper provides an overview of the use of the crowd simulation model for three main purposes; (1) as a modeling tool to simulate behavior of a crowd in different environments, (2) as a risk assessment tool to assess the risk posed in the environment, and (3) as an optimization tool to optimize the design of a building or space so as to ensure safer crowd movement and evacuation. Result shows that a simulation using the magnetic force model with a pathfinding feature provides a realistic crowd simulation and the use of ABC optimization can reduce evacuation time and improve evacuation comfort. This paper is expected to provide readers with a clearer idea on how crowd models are used in ensuring safer building planning and design.*

Keywords *– crowd modeling and simulation, crowd heat map, evacuation, fundamental diagram, optimum space design, path finding*

1. INTRODUCTION

Crowd is a collection of individuals present in a common environment at the same time that usually share some common goals. Each of the individuals may exhibit collective types of behaviors such as physical, psychological and social characteristics that influence the crowd to behave dynamically. According to [1], crowd exhibits highly complex dynamics and behaviors affected by crowd size, crowd demographics, crowd mobility, event location, location structure, weather conditions, etc. Therefore, adequate venue facilities and an effective crowd management plan must be in place as a large number of people gathering may lead to injuries or fatalities.

The development of crowd models has been very important in the investigation and study of crowd dynamics. Crowd modeling is a simulation study, where small to large numbers of movements of entities or individuals including their physical, social, psychological and behavioral factors and activities can be simulated. This paper is particularly important in predicting crowd behaviors in the virtual environment where experiments with humans are too dangerous to be tested and experimented with [2]. Thus, this model is capable of giving insight into human movement patterns and can be used by e.g. architectural engineers, designers or safety engineers, as a tool to assist them in buildings or facilities design before actual implementation [3]. This is why to date crowd modeling and simulation tools have been used widely in investigating crowd dynamics and behaviors.

Based on compilation of crowd disasters from 2011 to 2015 [4], there are two main causes of crowd disasters, and these are: (a) crowd behaviors, and (b) building designs. Therefore, addressing the issues of safer building or space design is vital to reduce the number of injuries and loss of lives that involve large crowds, especially during emergency situations. In general, there are three main approaches to evaluating building design safety effectiveness in terms of evacuation efficiency. These are the full-scale evacuation experiment [5], [6], following the prescriptive building codes approach [7], [8], and the use of crowd modeling and simulation approaches [9], [10]. The full-scale evacuation experiment is a practice to help building occupants to be familiar with the escape routes, evacuation procedures and processes when emergency occurs. It is straightforward but can be impractical as it can be dangerous if it involves large crowds, it is time consuming, and it only allows limited solutions to be proposed since any alterations to building layouts would be costly. The second approach to evaluating evacuation efficiency of a building is by checking the compliance of the building with the prescriptive building codes, which are documented standards and codes for building safety purposes that must be adhered to in building design [11]. This approach facilitates designer's work, but does not necessarily result in safe evacuations during emergency, and limits design freedom and flexibility. This is why in some countries the use of a crowd modeling and simulation approach has been introduced to overcome the limitations of the two approaches. This method can avoid injuries to humans as test subjects, it is convenient and reliable when used during the building design stage, and it can be used to evaluate safety performance of building pre-planning design. There are 3 main uses of crowd modeling, i.e., as a modeling tool, a risk assessment tool and an optimization tool. Each of these tools provides different objectives and analysis for crowd safety purposes. The simulation tool specifically focuses on simulating crowd dynamics including their behaviors based on real-life events [12], [13], [14]. The risk assessment tool is used to assess levels of safety of space filled with a crowd [15], [16], and in preparing action plans to minimize safety risks. For instance, the flow rate, congestion levels and speed density can be obtained and used in mitigating risks involving crowds. On the other hand, the optimization tool provides a systematic method to improve building design [17], [18], so that more efficient crowd evacuation can be achieved.

This paper discusses three important uses of the crowd modeling approach in ensuring a safer crowd. At the end of this paper, a discussion is given and a conclusion is drawn based on the results and in view of the findings.

2. USE OF CROWD MODELING IN BUILDING DESIGN

2.1. CROWD MODELING AND SIMULATION

Modeling crowd dynamics involves imitating the real crowd movement, including the activities and behaviors of the entities in the crowd in virtual environments. The entities in the crowd, known as 'agents', can interact and react with the simulated environment in order to imitate human movements. Such models can be used in the analysis of different types of crowd behaviors that emerge under normal or emergency situations. Crowd models are capable of giving insight into human movement patterns and are used by architectural engineers, designers or safety engineers, as a tool to used in building or facility design before actual implementation [3].

In general, crowd modeling is developed either at the macroscopic or the microscopic level. In the macroscopic approach, agents in the crowd are treated homogenously, where the internal and external characteristics of agents, such as speed, mass, position and other behaviors, are omitted. The microscopic approach focuses on the heterogeneous character of agents in the crowd and agent characteristics are included. In this method, modelers are able to assign different levels of agent granularity details, such as speed, current positions, destinations, etc. The physical force approach is one of the established modeling concepts for the microscopic approach. This approach is capable of integrating several intelligent features and behavioral factors to produce more natural and realistic agent movements.

2.1.1 HELBING'S SOCIAL FORCE MODEL

Many microscopic modeling approaches are based on the social force model (SFM) introduced by Helbing [19]. It is based on Newton's laws of motion, where the agents in a crowd are represented as particles or entities with their associated masses and velocities. By using Newton's equation represented in equations (1) and (2), agent movement will be influenced by three types of forces, i.e., the motivational force to move (f^0), the repulsion force between the agent and other agents (f_{ij}), and the repulsion force between the agent and the obstacle (f_{iw}). For f^0, the movement of each agent i with mass m^i will be influenced by agent's direction e^0 (t), its actual speed v_1 (t) and the desired speed $v^0_i(t)$ at the respective time τ_i. The rate of change of the agent velocity and the summation of the three forces can be calculated by using equation (3).

$$\sum F = m_i a \quad (1)$$

$$m_i a = f^0 + f_{ij} + f_{iw} \quad (2)$$

$$m_i \frac{dv_i}{dt} = m_i \frac{v_i^0(t) e_i^0 - v_i(t)}{\tau_i} + \sum_{j(\neq i)} f_{ij} + \sum_{w} f_{iw} \quad (3)$$

In addition to this, in order to represent the socio-psychological interactions in agent movements, the interaction of a repulsion force between agents, known as f_{ij}, can be included as shown in equation (4).

$$f_{ij} = A_i e^{\frac{(r_i - d_{ij})}{B_i}} n_{ij} + kg(r_{ij} - d_{ij}) n_{ij} + \kappa g(r_{ij} - d_{ij}) \Delta v_{ji}^t t_{ij} \quad (4)$$

The term $A_i e^{\frac{(r_i - d_{ij})}{B_i}} n_{ij}$ is a repulsion force, where A_i and B_i are constants, $d_{ij} = \|x_i - x_j\|$ is the distance between the center of body masses of agents i and j. The summation of body radius r_{ij} for agents i and j can be represented by $r_{ij} = r_i + r_j$. $n_{ij} = (n_{ij}^1, n_{ij}^2) = \frac{x_i - x_j}{\|x_i - x_j\|}$, which is the normalized vector pointing from agent j to i. When representing crowd dynamics under a panic situation, the agent body compression $k(r_{ij} - d_{ij})n_{ij}$ and a sliding friction force $\kappa(r_{ij} - d_{ij})$ have been introduced in the mathematical model, where k and κ are constants, $\Delta v_{ji}^t = (v_j - v_i)t_{ij}$ is the tangential velocity difference and $t_{ij} = (-n_{ij}^2, n_{ij}^1)$ represents the tangential direction. The function of $g(x)$ is equal to zero if the agents do not touch, where$(r_{ij} < d_{ij})$.

The interaction forces between the agent and the wall or obstacle w is given by equation (5), where d_{iw} represents the distance between agent i and the wall/obstacle, and n_{iw} and t_{iw} denote the perpendicular direction and the tangential direction to the wall, respectively.

$$f_{iw} = A_i e^{\frac{(r_i - d_{iw})}{B_i}} n_{iw} + kg(r_i - d_{iw}) n_{iw} + \kappa g(r_i - d_{iw})(-v_i t_{iw}) t_{iw} \quad (5)$$

2.1.2 MAGNETIC FORCE MODEL

As a modification of the original SFM, the modification was made by replacing f_{ij} with the magnetic concept by including the individual field of view (FoV) and the predefined boundary to repel. Therefore, a new equation for a basic individual movement to repel other individuals is given by the following formula:

$$f_{ij} = k_r \frac{M_i M_j}{x^2} n_{ij}, \quad (6)$$

where k_r is the repulsion constant, M_i and M_j are the social mass constants for the i^{th} and j^{th} individuals, respectively. Thus, j_{ij} is a normalized vector perpendicular to the individual. The repulsion constant k_r is represented by a positive number which can take any value between 0 and 10, i.e., $0< k_r \leq 10$. This range has been selected as it was suitable to represent the amount of a repulsion force to be exerted in the individual movement. As an initial assumption in this paper, M_i and M_j are assumed to be unity used to prove the similarity between the modified and the original models. To calculate the distance x between two individuals in equation (6), equations (7) and (8) are used:

$$D_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (7)$$

$$x = D_{ij} - R_i - R_j, \quad (8)$$

where $\{x_i, y_i\}$ and $\{x_j, y_j\}$ are the position coordinates of the i^{th} and j^{th} individual, respectively, R_i and R_j are the radii of the i^{th} and j^{th} individual, respectively, and D_{ij} is the distance between the center of the two individuals. Fig.1 shows how to calculate the distance between two individuals. From the modified model in equation (6), the condition for an individual to repel is based on its navigation FoV as well as the pre-defined comfort area, as depicted in Fig. 2

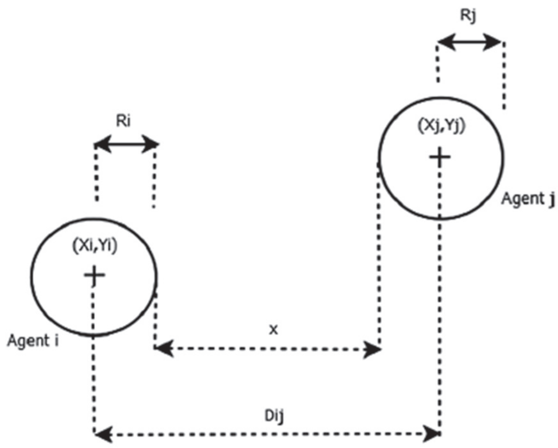

Fig. 1. Individual distance (from top view)

In the modified method, if an individual underlies within FoV and the pre-defined boundary to repel, denoted as A in Fig. 2, the latter will start to exert a repulsion force instantaneously. Otherwise, no repulsion force is exerted.

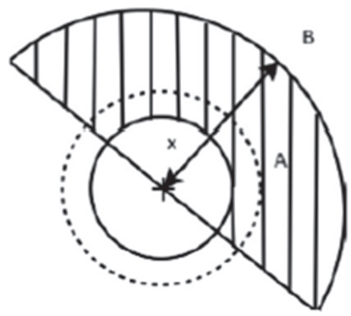

Fig. 2. Individual operation to repel (FoV)

By using the same strategy for calculating the repulsion forces among individuals described above, the repulsion force between an individual and an obstacle can be found in equations (9) and (10):

$$f_{iw} = \frac{k_w}{x_w^2} n_{iw} \,, \tag{9}$$

$$x_w = |r_i - r_w| \,, \tag{10}$$

where k_w is a constant, r_w is the individual distance checked based on the individual comfort area, and x is as described in equation (10). n_{iw} is the normalized vector perpendicular to the individual if the repulsion force is exerted, and r_i and r_w are the positions of the individual and the obstacle, respectively. Similarly to the range used for the repulsion constant k_r in equation (6), the range of k_w used in this paper is given by $0 < k_w \leq 10$. The strategy adopted to avoid obstacles is depicted in Fig. 3, where an additional normalized vector is introduced to calculate f_{iw} when an obstacle is encountered within the individual condition to repel. More precisely, the normalized vector, which is perpendicular to the obstacle, is included in the calculation of the new repulsion force to evade. This modification will guarantee that no body contact takes place between the individual and the obstacle.

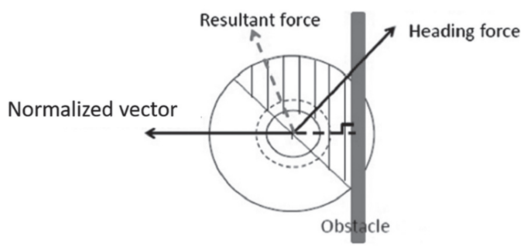

Fig. 3. Repulsion condition between an individual and an obstacle

2.1.3 MAGNETIC FORCE MODEL WITH PATHFINDING FEATURES

Path finding is proposed in this model as a modification of the original SFM. The aim of this feature is to guide an individual to select the shortest route towards its target destination. For this purpose, the Dijkstra Algorithm was adopted to achieve the pathfinding feature. This algorithm uses simplified node calculation in all individual movement directions. The Dijkstra Algorithm has been successfully used in various applications. Furthermore, this algorithm is fast and the node exploration propagates until the desired point is reached. Hence, it is adopted in this paper. Fig. 4 represents the flowchart of the Dijkstra Algorithm integrated with the proposed model.

For example, Fig. 5 shows how to find the shortest path agent from an origin to a destination by performing simple node calculation in all directions. Nodes A and B are assigned as initial and target nodes. The number in each circle will represent nodes and the interconnecting lines will represent the distance between each node.

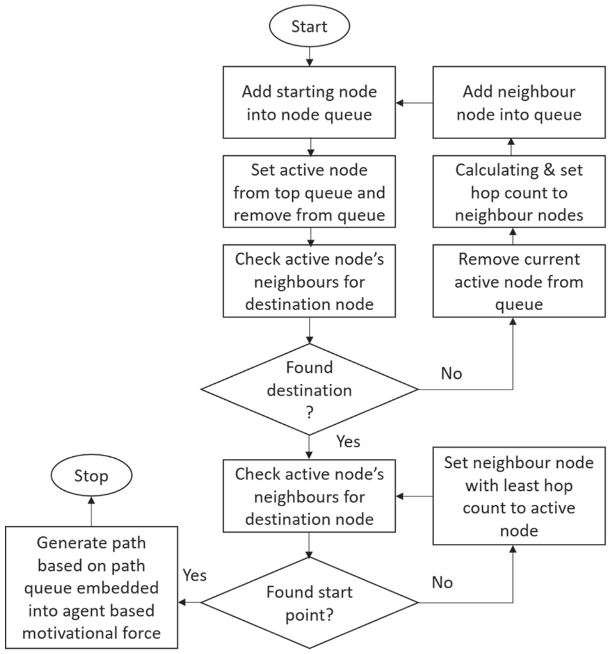

Fig. 4. Dijkstra algorithm flowchart

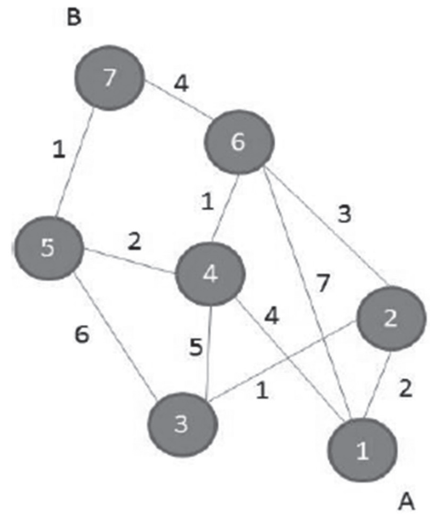

Fig. 5. Node assigns

In order for an agent to move from A to B via the shortest path, the distance between each node will be calculated from node A and the shortest distance will be chosen. In Fig. 5, the selected node is from node 1 to node 7 via nodes 4 and 5. The chosen nodes will be marked as visited nodes and this visited node will not be checked again. The application of this algorithm also guarantees that the agent will bypass these agents or obstacles in the shortest path in its waypoint towards the target point as shown in Fig. 6, where the black circle and the red star represent the agent and the target destination, respectively.

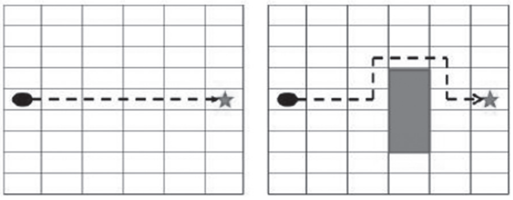

Fig. 6. (Left) Agent without an obstacle, (right) agent with an obstacle

2.2. RISK ASSESSMENT USING CROWD SIMULATION

The crowd simulation model has the ability to evaluate risks posed by building design, allowing the risks to be managed and mitigated through the insights provided. Examples of risk assessment tools for crowd dynamics include 'CRISP' and G-HES. CRISP is a fire risk assessment tool that uses Monte Carlo simulation of the entire fire and smoke spread scenarios as well as the human behavior model [19], [20], and the output of the model is evaluated based on the effect of toxic smoke. G-HES is a crowd evacuation model calibrated by using observations from live evacuation exercises [21]. It can be used to explore the consequences of a different number of people and evacuation procedures. Monte Carlo simulation is also used to provide the means of calculating the average and the worst-case evacuation times under different conditions. Other tools include the use of an expert system to assess fire safety [22], [23], and the use of the natural disaster risk assessment model for the tourism industry [24].

In SESAK, crowd simulation software developed at the Centre for AI & Robotics, Universiti Teknologi Malaysia, the risks that might occur in a crowd are evaluated based on the crowd congestion and discomfort levels. The information is visualized by using a heat map and graphical evacuation performance.

2.3. BUILDING DESIGN OPTIMIZATION BY USING THE CROWD SIMULATION MODEL

Addressing the issues of safer building or space design by providing good space layout is vital to reduce the number of injuries and loss of lives during emergency situations. During the building design stage, the use of the crowd modeling and simulation algorithm can provide useful feedback on emergency evacuation risks or even human comfort in the building before the building is constructed or any structural modifications are made. This can significantly reduce the risk and expensive alteration costs. Optimal design of building space for safer evacuation in this paper uses the Artificial Bee Colony (ABC) optimization algorithm and crowd dynamics modeling to determine optimal locations of the exit doors.

2.3.1 SINGLE-OBJECTIVE OPTIMIZATION

The optimization algorithm inspired by swarm intelligence has become increasingly popular in solving complex (NP-hard) problems. Swarm intelligence optimization algorithms mimic social movement and behavior (swarming and flocking) of biological systems such as birds, fish and bees. The ABC optimization algorithm introduced by Karaboga [25] is one of the robust swarm intelligence algorithms used to solve real-world optimization problems. The structure of the ABC algorithm is based on foraging behavior of honey bees, where the colony of artificial bees in the ABC algorithm consists of three groups of bees; namely, employed bees, onlookers and scouts. In the ABC algorithm, the food source position represents a possible solution to the related problem; meanwhile, the nectar amount of the food source corresponds to the quality (fitness) of the associated solutions [26].

The ABC algorithm is employed to optimize the locations of the exit doors for the multiple room building layout as shown in Fig. 7, so as to achieve minimum evacuation. A single objective, one-dimensional optimization problem (to determine exit door locations) is considered. The exit door widths are maintained at 1 m throughout simulation and optimization evaluation. The SFM is used to evaluate the fitness value or quality (evacuation time) of the solutions (exit door locations) provided from the ABC algorithm.

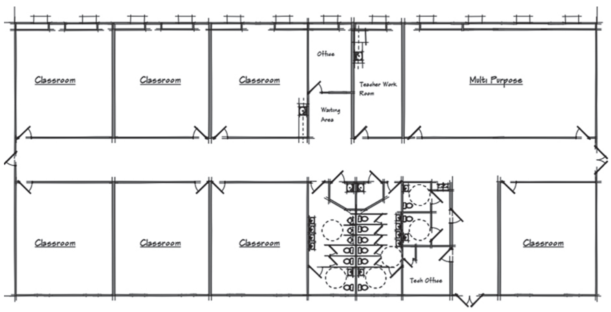

Fig. 7. Multiple room building layout

A flowchart for the optimization process is illustrated in Fig. 8. There are 3 types of control parameters which need to be initialized in the ABC algorithm, and these parameters are the number of food source, the limit and the number of iterations.

From the flowchart shown in Fig. 8, it can be observed that the algorithm has 4 main phases, i.e., the initialization phase, the employed bees phase, the onlooker bee phase and the scout bee phase.

Firstly, the user needs to define the value of control parameters involved in the ABC algorithm, which are exit door locations, the limit and the number of iterations. Exit door locations are randomly initialized by using equation (11) in a given search space area.

$$x_{n,i} = l_i + rand(0,1) * (u_i - l_i), \tag{11}$$

where $x_{n,i}$ represents the value for the i^{th} dimension, where i = 1,....,D (D = the number of optimization parameters), and the n^{th} solution, where n = 1,....,SN (SN = the number of solutions). x_{ni} is bounded between a specified lower value $l_i = 0$ and an upper value u_i = ***Room Lenght***. Fig. 9 and Table 1 represent the offset value for exit door locations in the environment according to the bounded region.

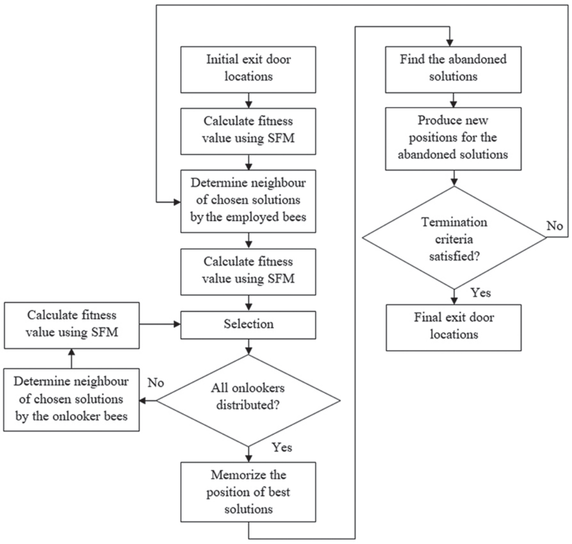

Fig. 8. Flowchart optimization – simulation by using the SFM and the ABC optimization algorithm

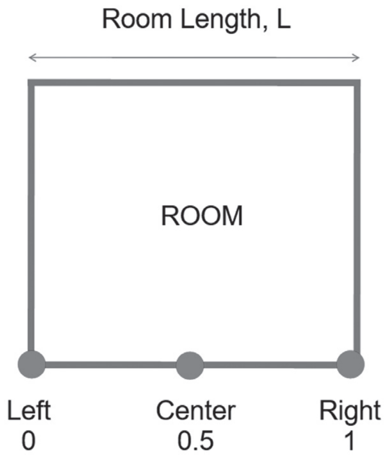

Fig. 9. Representation of offset door location

Table 1. Calculation for the offset door location

Door offset location	Door location in actual length
Left, 0	*= 0 × Room Length*
Center, 0.5	*= 0.5 × Room Length*
Right, 1	*=1 × Room Length*

After that, $x_{n,i}$ are evaluated by using the SFM of the crowd through equations (1) – (5) and the objective function of evacuation time values is calculated.

For employed bees, door location within the neighborhood of the previous solution is calculated by using equation (12).

$$v_{n,i} = x_{n,i} + \emptyset_{n,i}(x_{n,i} - x_{m,i}) \tag{12}$$

From the equation, $m \in (1,...SN)$, where $m \neq n$ and $i \in (1,...D)$ are randomly chosen indexes. $\emptyset n,i$ is a random number within the range [-1,1]. After producing new exit door locations v_n, again, the objective function is calculated by using the SFM. Next, roulette wheel selection is applied between the values of x_n and v_n. By using equation (13), the fitness value from the solution $fit(x_n)$ can be calculated based on the objective function value $f(x_n)$.

$$fit(x_n) = \begin{cases} \frac{1}{(1+f(x_n))} & if \;\; f(x_n) \geq 0 \\ 1 + abs(f(x_n)) & if \;\; f(x_n) < 0 \end{cases} \tag{13}$$

Next, an onlooker retrieves and exploits the solution information by calculating the probability p_n by using equation (14) and evaluated by using the SFM.

$$p_n = \frac{fit(x_n)}{\sum_{n=1}^{SN} fit(x_n)} \tag{14}$$

Finally, a scout bee will determine the abandoned solution by evaluating the limit parameter. If it exists, the scout bee will find a new random solution by using equation (11).

2.3.1 MULTI-OBJECTIVE OPTIMIZATION

The aim of most cases in multi-objective optimization problems is to search for the maximum or the minimum value of the cost function as the target solution. Since there is more than one objective function involved, multi-objective problems become harder to solve by using the single-objective optimization algorithm. In these problems, there is no unique solution, i.e., a set of acceptable trade-off optimum solutions is produced by using the Pareto front. One objective is sacrificed if an improvement on the other objective is to be made [27]. This process will be repeated iteratively until there is no better solution available. Therefore, a curve of the Pareto optimal front is produced and this value will be chosen as the final result of optimization.

The Multi-Objective Artificial Bee Colony (MOABC) algorithm is employed to optimize exit door locations for the factory layout so as to achieve minimum evacuation time to evacuate and the discomfort level. Multi-objective optimization with a one-dimensional problem (to determine positions of the exit doors) is considered. The size of the doors is maintained at 1 m throughout simulation and optimization evaluation. The fitness value or the quality (evacuation time and the discomfort level) of the solutions (exit door locations) is evaluated by using the SFM.

This algorithm consists of 5 phases, which include the initialization phase, the employed bee phase, the onlooker bee phase, the scout bee phase and the archive update. Firstly, define the values of control parameters involved in the algorithm, which are the number of population (exit door locations), the limit, the number of iterations and the fixed archive size. The exit door locations are randomly initialized by using equation (11).

Next, the solutions retrieved from $x_{n,i}$ will be evaluated by using the SFM equations (1) – (5), and the objective function values of the evacuation time and the discomfort level from equation (15) are calculated. The best solutions will be stored inside a fixed archive size.

$$D = \frac{1}{N}\sum_{i}\frac{\overline{(v_{1} - \overline{v_{1}})^2}}{(\overline{v_{1}^2})} = \frac{1}{N}\sum_{i}\left(1 - \frac{\overline{v_{1}}^2}{(\overline{v_{1}^2})}\right) \quad (15)$$

The employed bee phase will use the best archive solutions and create its own solution. This calculation can be done by using equation (12) and updating the non-dominated solutions in the archive. Next, the onlooker bee needs to choose the solutions from the employed bee by calculating the probability ***Pk*** using the following equation:

$$P_k = \frac{\text{fit}\,(x_m)}{\sum_{m=1}^{\text{Solution number}} \text{fit}\,(x_k)}, \quad (16)$$

where $fit(x_k)$ is the probability of the solution proposed by the employed bee m proportional to the quality of the solution. $fit(x_k)$ can be formulated by using equation (17).

$$\text{fit}\,(x_k) = \frac{\text{dom}(k)}{\text{Solution Number}}, \quad (17)$$

where $dom(k)$ is the function that returns the number of solutions dominated by solution k. Next, the onlooker bee will choose the probability by using roulette wheel selection and randomly choosing the candidate in the archive. Finally, a new position will be calculated by using equation (11), and then this position objective function will be obtained by using the SFM equations (1) - (5) and (15). If the solution dominates the old value, the solution will be updated in the archive.

The scout bee will determine the abandoned solution by checking the limit parameter that was previously defined in the initialization phase. If the maximum trial limit for a given bee is reached, that bee becomes a scout bee that will find a new exit door position using equation (11), evaluate the objective function and check whether the solution dominates the archive value or not. If this condition is satisfied, the solution will be replaced, otherwise, the old value remains in the archive.

An archive is a place where all best solutions are compared and stored by using the non-dominated algorithm as shown in equations (18) – (21). In each iteration and through each phase involved in the MOABC, every new solution will be compared with other solutions to omit any dominated solution so only the best solution (non-dominated) is maintained in the archive. From here, the Pareto front can be plotted, where it shows the best solutions inside the archive.

$$\text{Evacuation time} : \min f_i(x)$$

$$\text{Discomfort level} : \min f_j(x)$$

$$x^* \in \mathbb{S}$$

$$i \neq j,$$

$$f_i(x) = f_i(x^*), f_j(x) < f_j(x^*),$$

where

x = a decision variable position vector,

x^* = a non-dominated solution of a multi-objective optimization problem,

$\mathbb{S}$ = a feasible region in the search space.

3. SIMULATION RESULTS

3.1. CROWD MODEL SIMULATION

In this section, we discuss a numerical simulation analysis based on the following two types:

(i) Qualitative analysis: through observing the effect of collective behaviors,

(ii) Quantitative analysis: the fundamental diagram of crowd density and flow rate.

3.1.1 SIMULATION BY USING HELBING'S SOCIAL FORCE MODEL

Clogging behavior is more likely to occur in a crowd of higher density. In this situation, when passing through a narrowed exit such as the door, a denser crowd will cause a slower individual to move with difficulty. The exit door becomes clogged, while the crowd forms an arch shape as depicted in Fig. 10

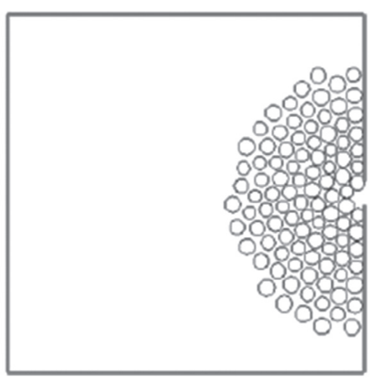

Fig. 10. Clogging and arching behavior at a narrow exit door

3.1.2 SIMULATION BY USING THE MAGNETIC FORCE MODEL

By replacing the original mathematical model with the magnetic approach in the SFM, a collective type of crowd behaviors can be observed in the simulation results. Figures 11, 12 and 13 show how simulation using the Magnetic Force Model is able to demonstrate the phenomena of corner hugging, lane formation and counter flow.

Fig. 11. (left) Corner hugging from real data, (right) Corner hugging from simulation

Fig. 12. (left) Lane formation from real data, (right) Lane formation from simulation

Fig. 13. (left) Counter flow from the video, (right) Counter flow from simulation

For quantitative analysis, as the number of people per square meter increases, people cannot take whole paces forward. The movement starts to contrast, and the flow rate drops as shown in figures 14 and 15. When the density increases, the flow rate increases until the critical density is reached (2 – 3 people per square meter). This critical density may vary according to different events/crowd sizes.

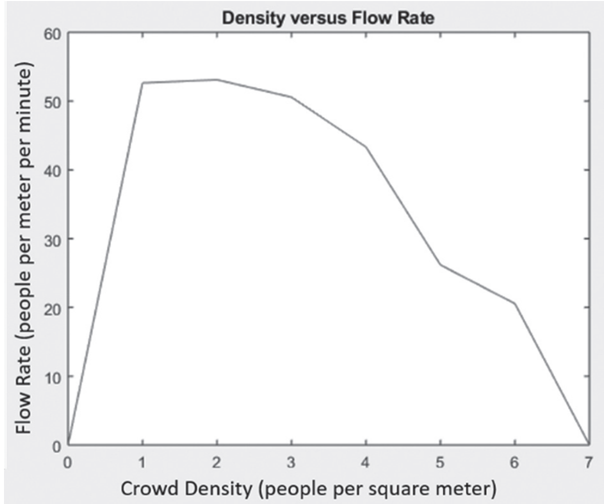

Fig. 14. Crowd density versus flow rate (1m)

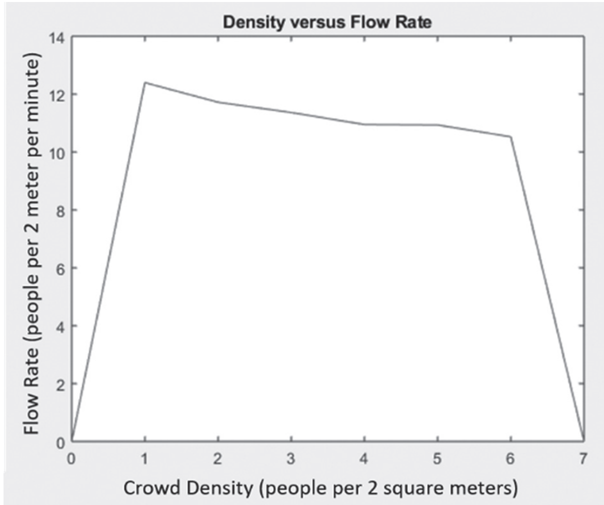

Fig. 15. Crowd density versus flow rate (2m)

3.1.3 SIMULATION BY USING THE MAGNETICFORCE MODEL WITH A PATHFINDING FEATURE

To test the effectiveness of the proposed pathfinding feature in the model, we have considered multiple rooms on a single floor in the simulation environment. There are 6 rooms (5m x 5m) with one main exit constructed in the model as represented in Fig. 16.

All individuals will escape from each room by moving towards the main exit door. The size of each room and the main exit door was 1 m, which is the standard door size in residential/office buildings. For initial testing we used 6 individuals randomly placed in the rooms. The individuals used the generated waypoint from the Dijkstra Algorithm to move towards the main exit door. The total time taken and generated waypoints for them to move towards the main exit door have been compared with the original SFM. The experiment was repeated 5 times by changing the initial individual position in the environment randomly. The result is depicted in Table 2.

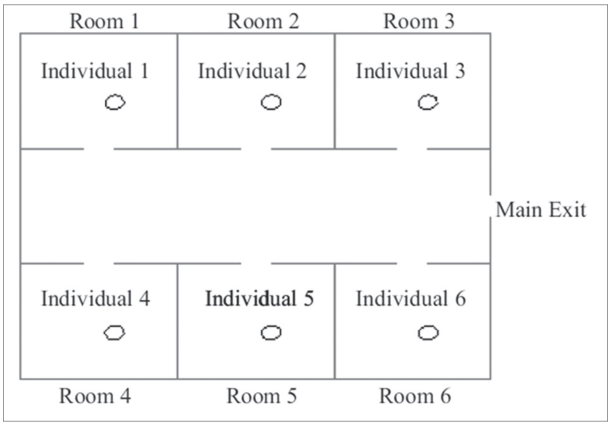

Fig. 16. Multiple room environment

Table 2. Comparison of total time taken to escape in terms of the Magnetic Force Model and the original SFM model

Experiment	Magnetic Force Model	Original SFM
1	11.5 s	
2	11.7 s	
3	11.9 s	The task was not completed – no pathfinding feature
4	12.2 s	
5	12.0 s	

By using the pathfinding feature integrated with the proposed model, the time taken for all individuals to evacuate through the main exit door is in between 11.5 and 12.2 s. A waypoint generated from the Dijkstra Algorithm will be used for finding the shortest path for an individual in evacuate route selection. Meanwhile, by using the original SFM, the task for the individual to evacuate safely through the main exit was not completed. This is because the waypoint for the pathfinding feature of an individual to move in a complex environment was not defined in the model. Other than that, individual movement was treated as a particle to move to search for the target destination without guidance; thus, it will take more time to end the simulation. Furthermore, it will not represent how a real individual will behave in the crowd.

3.2. RISK ASSESSMENT CALCULATION & VISUALIZATION

By running the simulation in SESAK, both 2D and 3D visualizations are available for viewing. This software uses an efficient Magnetic Force Model algorithm in identifying congestion levels in the space by visualizing a color heat map. The color heat map will give information to the user on which area or space is likely to be unstable and congested and what action plan can be taken to minimize the problem. Fig. 17 represents a color heat map in simulation software.

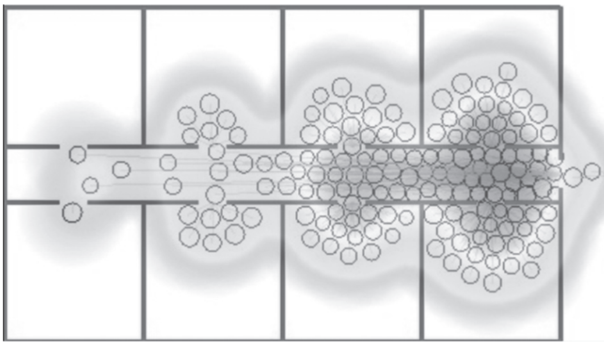

Fig. 17. Congestion level heat map in 2D visualization

In addition, this software can also provide crowd analytics tools to analyze evacuation performance such as the number of people evacuated and the evacuation time as depicted in Fig. 18.

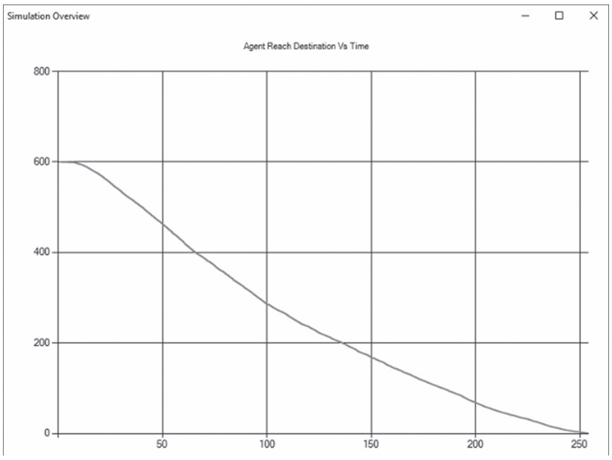

Fig. 17. Evacuation performance graph (agent reach destination vs. time)

3.3. SPACE DESIGN OPTIMIZATION TOOL

3.3.1 SINGLE OBJECTIVE SIMULATION RESULTS

The single objective ABC optimization algorithm has been used to provide optimal locations of the exit doors for multiple room layouts as shown in Fig. 7. The layout size is set to 12m x 12m and for the number of individuals it is set to 64 randomly distributed people. The objective function is the evacuation time and it is evaluated by using the SFM. The simulation was processed by using a Personal Computer (PC) with Intel® Core™ $i7$ - 4770 CPU and a 16 - GB RAM memory. The initial control parameters for the number of exit door locations, the limit and the maximum number of iterations have been set to 10, 50 and 300, respectively. This is the basic initial value used to evaluate the performance of the proposed optimizer to solve the application problems. The algorithms were simulated 30 times with different random initial positions of the crowd. Fig. 19 shows the number of evacuated people with the evacuation time. It shows that the total number of evacuated people based on optimized design has improved drastically, i.e., 32% faster than non-optimized design for the crowd to finish evacuation. The ABC optimization algorithm is capable of finding optimum locations of the exit door for multiple room building layout, which can improve the evacuation efficiency and the numbers of evacuated people. Instead of using a manually tuned method, the designers can use the proposed optimizer to help them with the building design stage and to speed up the decision-making process.

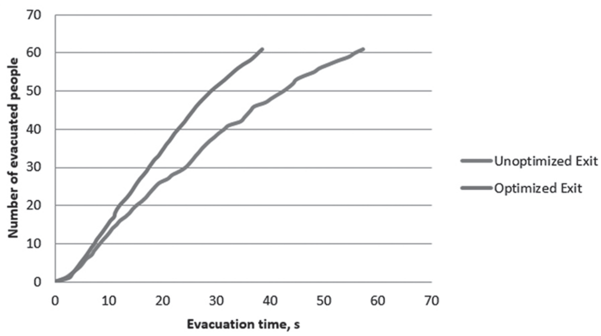

Fig. 19. Comparison of the number of evacuated people for optimized and unoptimized exit door locations

3.3.2. MULTI-OBJECTIVE SIMULATION RESULTS

For a multi-objective problem, Fig. 20 represents multiple room layout used as our experiment test. The layout size is set to 30m x 15m and for the number of individuals, we take a maximum of 60 people that can occupy the space. The locations of the individuals will be randomly distributed in the environment. The number of exit door locations, limit, maximum iterations and archive is set to 10, 50, 100 and 30, respectively.

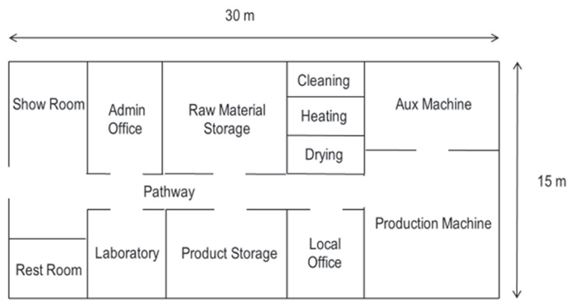

Fig. 20. Original layout of exit door locations

The objective function in the multi-objective problem is the evacuation time and the discomfort level and it is evaluated by using the SFM. Simulation was processed by using a Personal Computer (PC) with Intel® Core ™ i7-4770 CPU. Fig. 21 illustrates the Pareto front for the best solutions stored in the archive. The user can freely choose from the Pareto set whose results will satisfy the needs. Table 3 below shows a comparison of multi-objective solutions for the evacuation time and the discomfort level from the original design and those proposed by the optimizer.

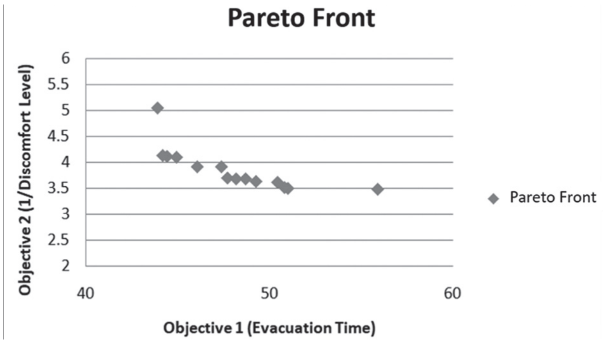

Fig. 21. Pareto front best solutions

Table 3. Comparison of total time taken to escape in terms of the Magnetic Force Model and the original SFM model

	Door Location	Evacuation Time	Discomfort
Original layout	Center	51.45 s	0.243
Proposed by the optimizer (Pareto front)	Left	44.21 s	0.242

In order to analyze and compute the performance for the proposed exit door locations by the multi-objective optimizer and the original exit door locations, a detailed analysis of the number of people who left at different evacuation times is depicted in Fig. 22. The result clearly shows that by using the optimizer, the proposed exit door locations resulted in the improved evacuation time. People leave more quickly by using the proposed solutions from the Pareto set due to lower body compression to escape in front of the main exit door. If higher body compression occurs in front of the main exit door, it will cause a higher discomfort level and hence a delay in time for the crowd to evacuate.

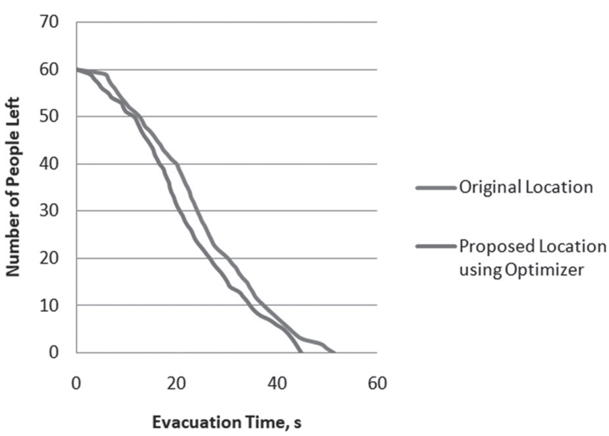

Fig. 22. Comparison of the number of people who left vs. evacuation time between the original layout and proposed by the optimizer

4. CONCLUSIONS

Crowd modeling and simulation are a tool to understand how crowds behave in different environments. They can also be used to prepare for an effective crowd management plan, to assess risks posed by certain space designs and to design space optimized for better evacuations. The microscopic crowd modeling approach using the magnetic force model allows various agent characteristics to be included for more realistic crowd simulation, to be computationally more efficient and to be flexible enough to include cognitive capability such as the pathfinding feature in the model. This paper has also shown that various information can be extracted from the simulation model such as evacuation time, the comfort level, risks of congestion and a crowd flow pattern at different locations. Integration with an optimization algorithm enables a designer to come up with optimum space design that can reduce the evacuation time and crowd discomfort simultaneously.

5. ACKNOWLEDGEMENT

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