Agent-based evacuation model incorporating life jacket retrieval and counterflow avoidance behavior for passenger ships

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Abstract. In actual evacuations, passengers should collect their life jackets before moving toward assembly stations. Passengers who do not wear life jackets must return to their cabins to collect their life jackets, as this equipment is usually stocked in individual cabins. However, current studies ignore the behavior of collection and donning of life jackets exhibited by passengers initially walking to the assembly station without life jackets. In order to investigate the influence of the collection of life jackets on the evacuation, an agent-based social force model is proposed. This model incorporates the collection and donning of life jacket, following behavior, and counterflow avoidance behavior. The model was validated by the International Maritime Organization (IMO)’s counterflow test, and satisfied its requirements. The fundamental diagram of the bidirectional flow of our model was validated against the results of a previous study. The results show that this model can reproduce collective phenomena in pedestrian traffic, such as dynamic multilane flow and stable separate-lane flow. Finally, the model was applied to deck 5 of a passenger ship. It was found
that the evacuation time with life jackets is much longer than that without life jackets if some passengers are not in their cabins before the evacuation. It was also found that reducing the number of passengers who have to undergo life jacket retrieval can greatly increase evacuation efficiency. Moreover, we provide two optimized evacuation schemes for ship designers. These findings offer ship designers some insight towards increasing the safety of large passenger ships.

Keywords: agent-based models, traffic and crowd dynamics

1. Introduction

A passenger ship is a complex transportation vehicle. Its complexity has been increasing with the development of the shipbuilding industry. The safety of large passenger ships has gained considerable attention in the last few decades. The International Maritime Organization (IMO) Maritime Safety Committee (MSC) has developed guidelines for the evacuation of passengers. The latest set of guidelines is the IMO MSC/Circulation 1533 (MSC.1/Circ.1533) [1], which provides revised guidelines on evacuation analysis for new and existing passenger ships. These guidelines make evacuation analysis
mandatory not only for roll-on/roll-off passenger ships, but also for other passenger ships constructed on or after January 1, 2020.

Recently, Zheng et al [2] summarized systematically crowd evacuation models based on seven methodological approaches and discussed the advantages and disadvantages of these approaches. Proceeding from the model scale [2], the pedestrian flow models can be classified into macroscopic models [3, 4] and microscopic models [5–13]. The former ones treat a crowd of pedestrians as a whole with a focus on macroscopic behaviors such as density, average speed and pedestrian flow. And the macroscopic model is generally based on traffic flow, queuing theory, or fluid or continuum mechanics. The microscopic models focus on the features of pedestrian movement details and the behavioral characteristics of each individual in the crowd. Microscopic models are usually based on the social force models [5, 6], cellular automaton models [8–10] or agent-based models [11–13]. The latest trend [2] in relevant researches indicates that the crowd evacuation should be studied by combining various approaches, such as the agent-based model based on cellular automaton [14] and the agent-based models based on social force [15, 16].

In the original social force model, pedestrians do not try to avoid the oncoming pedestrian flow, which leads to unreal collisions. However, some modified social force models have been developed to solve that problem. For example, Smith et al [17] added a component to the desired velocity of the social force model to avoid possible collisions. Lee et al [18] added following effects and evasive effects to the social force model to explain the bidirectional flow. In the above two models, pedestrians can only avoid collisions with one pedestrian at a time; hence, these models may not able to produce realistic behavior in dense crowds. Jiang et al [19] extended the social force model with dynamic navigation field, which needs to be calculated within each time step, so the computational overhead increases during the simulation. Heliövaara et al [20] divided the area in front of the agent into three overlapping sectors and selected the direction of the sector with the highest calculated score as the direction of motion. In this model, a pedestrian can avoid collisions with multiple pedestrians simultaneously. Calibrating this model, however, is challenging because it involves numerous parameters and discrete dodging directions (straight on, right, and left).

The original social force model could show the crowd behaviors, such as the ‘faster is slower’ effect, inefficient use of alternative exits, oscillations of the passing direction at a bottleneck, and lane formation. However, it does not provide any decision-making capabilities for pedestrians [21]. Reynolds [22] proposed a crowd behavior including cohesion behavior (move to a group location), alignment behavior (move along the direction that the group moves), and separation behavior. This crowd behavior has been widely applied to evacuation simulations [16, 23–26].

Computer simulation is being increasingly used in the ship design industry to analyze passenger ships. For example, Ha et al [23] used simulations for advanced evacuation analysis using a cell-based model of a passenger ship. This model incorporates individual behavior (that is represented by the body shape, walking speed, walking direction, and rotation of each passenger), crowd behavior (the tendency that people want to act together with other people), and counterflow avoidance behavior (that is, the behaviors of passengers avoiding other passengers moving in the opposite direction) of the passengers. Roh et al [24] applied a cell-based simulation model for an
advanced analysis of a car ferry with 2487 persons. Park et al. [26] further validated the abovementioned model by using experimental data collected from real evacuation trials conducted in two full-scale ships. Cho et al. [25] presented a velocity-based evacuation model, which includes individual, crowd, and counterflow avoidance behaviors. In addition, the above models [23–26] were applied to 11 tests specified in IMO MSC.1/Circ.1238 [27], and their results indicated that all the requirements of these tests have been met. Yuan et al. [28] proposed a neighborhood particle swarm optimization evacuation model for passenger ships; their model considered individuals as particles and incorporated the effects of movement of ships. Chen and Han [29] proposed a new multigrid model based on cellular automata with a fine lattice to enhance the continuity of trajectories of passengers in the evacuation simulation of passenger ships. Casareale et al. [30] applied a social force model approach including way-finding issues and signage effects to simulate the Costa Concordia accident. They confirmed that the way-finding solution can increase the efficiency of the evacuation process in complex architectural spaces such as cruise ships. Moreover, they demonstrated that computer simulation can aid the ship design process and preparation of safety guidelines. It is also useful to crewmembers during naval emergency management training. Some of these models include its own counterflow model; however, these models [23–26, 28] were only verified by Test 8 (counterflow) from IMO MSC.1/Circ. 1238 [27]. Further, the studies listed above did not consider the behavior of returning to cabins and the collection and donning of life jackets, which may cause counterflow.

Note that the evacuation scenarios in MSC.1/Circ.1533 (Revised version of MSC.1/Circ.1238) only include the situation that 8.3% of the crew proceed toward the most distant passenger cabin in the counterflow with passengers. Further, no scenario has incorporated life jacket retrieval. In an actual evacuation, passengers first get their life jackets and then begin to walk along escape routes to predefined assembly stations. The life jackets usually are stocked in each cabin to save space. The life jackets may be stocked in the seats or muster stations in some small ships due to the fact that these ships are designed for short trips and do not provide accommodation (e.g. some small roll-on/roll-off ferries). Passengers in the cabin need to spend some time collecting their belongings and life jackets [25, 30]. An easy way to simulate such behavior is to modify their pre-movement time [31]. However, those passengers who are not in cabins must return to their cabins. Counterflow occurs when these passengers encounter others moving toward the assembly station. Meanwhile, some of the crew also need to search the cabins for passengers who are still inside the cabins.

Our previous model [16] is not well suited for bidirectional flow. When two agents move in different directions and their paths cross, the two agents will collide head-on and will not dodge to the left or right. This scenario is inconsistent with the actual situation. Hence, we propose a new agent-based social force model based on our previous work [16] by adding a counterflow model. The core idea of our counterflow model is derived from the model of Heliövaara et al. [20]. We made some modifications to realize realistic counterflow model that is easy to calibrate. Unlike the traditional evacuation model, our model can reproduce the behavior of passengers returning to their cabins to collect and don life jackets. Our research addresses this lack in traditional models and provides a solution for ship design based on IMO guidelines by considering life jacket retrieval behavior. However, actual evacuation may be more complex than our
simulation; for example, our simulation does not account for the time taken to free and

don a life jacket and in an actual scenario, more than one deck on a ship may have to

be evacuated.

This paper is organized as follows. In section 2, we describe the counterflow model,

the preparation work for simulations, and the simulations. Section 3 presents the

verification of the model through test 8 in MSC.1/Circ.1533 [1] and based on experi-

ments in literature [32]. Section 4 presents the evacuation simulation results with life

jacket retrieval on deck 5 of a passenger ship. The conclusion is given in section 5.

2. Methodology

This study consists of the following three main phases:

(1) Model definition

The model was proposed based on our previous work [16] by combining a counter-

flow model. The counterflow model was inspired by the model of Heliövaara et al

[13].

(2) Verification tests

This was accomplished through a qualitative verification a quantitative verifica-

tion. The qualitative verification was performed by the IMO test 8 specified in

MSC.1/Circ. 1533 Annex 3 [1]. The quantitative verification was achieved by

comparing the fundamental diagram of the experiment [32] with our simulation

results.

(3) Application to a case study and evaluations

Evacuation simulations were conducted on deck 5 of a passenger ship early in its

eyearly design stage. Results helped quantify how the behavior of collection and

donning of life jackets affected evacuation process.

2.1. Model

2.1.1. Counterflow model. As mentioned in the introduction, the core idea of our

counterflow model is derived from the model of Heliövaara et al [13]. They divided the

area in front of an agent into three overlapping sectors and selected the direction of

the sector with the highest calculated score as the movement direction. As the speed

of an agent increases, the range of their sectors extends from 1.5 m to 3.0 m. And as

that speed decreases, the angle of their sectors increases from 80 degrees to 90 degrees.

In order to make our model easy to calibrate, we calculated the cost instead of the

score for each sector, and adopted fixed values for the range and angle of the sectors.

In order to make the counterflow model more realistic, we added two sectors ($S^F$ and

$S^S$, see figure 1(b)) to our model and changed the dodging direction from three discrete
directions to continuous direction.

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Our counterflow model contains two types of behaviors: following behavior and counterflow avoiding behavior. The following behavior causes an agent to follow others walking in the same direction in front of it. If an agent is in counterflow and there is no one in front with the same moving direction, the counterflow avoiding behavior will cause the agent to dodge to the right.

In the counterflow model, we selected five test vectors \( \mathbf{U}_i = \{ \mathbf{u}_i^L, \mathbf{u}_i^{LF}, \mathbf{u}_i^F, \mathbf{u}_i^{RF}, \mathbf{u}_i^R \} \) that point to the left, left front, front, right front, and right, respectively, as shown in figure 1(a). Five overlapping sectors \( S_i = \{ S_i^L, S_i^{LF}, S_i^F, S_i^{RF}, S_i^R \} \) each cover a 60° wide sector around the test vectors \( \mathbf{U}_i = \{ \mathbf{u}_i^L, \mathbf{u}_i^{LF}, \mathbf{u}_i^F, \mathbf{u}_i^{RF}, \mathbf{u}_i^R \} \), respectively, as shown in figure 1(b). The front test vector \( \mathbf{u}_i^F \) is the unit vector in the direction of the current velocity \( \mathbf{v}_i \) of agent \( i \). The evaluating sector \( S_i^E \) covers a 160° wide sector around the front test vector, and it is used to determine whether the agent is in the counterflow. The set of other agents in the evaluating sector is given by

\[
S_{i-P}^E = \left\{ j \mid j \in P, j \neq i, | \mathbf{p}_j - \mathbf{p}_i | < R^S, \arccos \left( (\mathbf{p}_j - \mathbf{p}_i) \cdot \mathbf{u}_i^F \right) < \frac{4\pi}{9} \right\}
\]  

(1)

where \( R^S \) is the radius of all the sectors. \( P \) denotes the set of all agents. \( \mathbf{p}_i \) and \( \mathbf{p}_j \) denote the position vectors of agent \( i \) and \( j \).

The core idea of the counterflow model is to select a sector with the least counterflow. If at least one counterflow agent is in the evaluating sector, it selects the sector with the smallest total cost among all the sectors, \( S_i = \{ S_i^L, S_i^{LF}, S_i^F, S_i^{RF}, S_i^R \} \), 6 times s\(^{-1}\). For any test vector \( \mathbf{u}_i^* \in \mathbf{U}_i \), the basic cost of its sector \( S_i^* \in S_i \) is given as follows:

\[
C_i^* = \arccos \left( \mathbf{c}_i^E \cdot \mathbf{u}_i^* \right) f \left( n_i^{*-c} \right)
\]

(2)

where

\[
\mathbf{c}_i^E = \sum_{j \in S_{i-P}^E} \frac{\mathbf{p}_j - \mathbf{p}_i}{n_i^E - c} f (\mathbf{u}_i^0 \cdot \mathbf{u}_j^0)
\]

(3)

\[
f (x) = \begin{cases} 
1 & x > 0 \\
0 & x \leq 0
\end{cases}
\]

(4)

\( \mathbf{c}_i^E \) is the vector toward the center of mass of the agents in the evaluating sector \( S_i^E \) who are not in counterflow; \( n_i^E - c \) is the number of non-counterflow agents in the evaluating sector \( S_i^E \); \( n_i^{*-c} \) is the number of counterflow agents in the test sector \( S_i^* \); target direction \( \mathbf{u}_i^0 = \mathbf{v}_i^0 / |\mathbf{v}_i^0| \) is the unit vector of the desired velocity \( \mathbf{v}_i^0 \) (toward an exit or a target point). If two agents are in a unidirectional flow, the inner product of their target directions \( \mathbf{u}_i^0 \cdot \mathbf{u}_j^0 \) is bigger than 0; else, \( \mathbf{u}_i^0 \cdot \mathbf{u}_j^0 \) is less than 0 (counterflow). In general, the basic cost of any test sector \( S_i^* \) is the angle between its test direction \( \mathbf{u}_i^* \) and average position vector \( \mathbf{c}_i^* \) of non-counterflow agents in the evaluating sector \( S_i^E \), except that the test sector \( S_i^* \) does not lead to counterflow (i.e. \( n_i^{*-c} \) is equal to 0).

The total cost for any sector \( S_i^* \in S_i \); its total score is the combination of its base score and its weight given as follows:
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\[ T^*_i = C^*_i + c^L h \left( \left| u^*_i - u^L_i \right| \right) + c^{LF} h \left( \left| u^*_i - u^{LF}_i \right| \right) + c^F h \left( \left| u^*_i - u^F_i \right| \right) \\
+ c^{RF} h \left( \left| u^*_i - u^{RF}_i \right| \right) + c^R h \left( \left| u^*_i - u^R_i \right| \right) \]

where

\[ h(x) = \begin{cases} 1 & x = 0 \\ 0 & x \neq 0 \end{cases} \]

\[ c^L, c^{LF}, c^F, c^{RF}, \text{ and } c^R \] are the preference factors for test sectors \( S^L_i, S^{LF}_i, S^F_i, S^{RF}_i, \text{ and } S^R_i \), respectively. When all the total costs are obtained, the model selects the sector with the lowest total cost, and then it selects the vector \( c_i \) toward the center of mass of the non-counterflow agents in selected sector \( S^{Se}_i \) as the movement direction.

\[ c_i = \sum_{j \in S^{Se}_i} \frac{p_j - p^E_i}{n^{Se\_nc}_{S^{Se}_i}} f \left( u^0_j \cdot u^0_i \right) \]

where \( n^{Se\_nc}_{S^{Se}_i} \) is the number of non-counterflow agents in selected sector \( S^{Se}_i \). An agent is a local leader if there is no agent in the evaluating sector \( S^E_i \) who is in non-counterflow (\( n^{E\_nc}_{S^E_i} = 0 \)). The above model only describes the following behavior of the agent who is not a local leader. If an agent is a local leader, the agent prefers right (the test sector \( S^{RF}_i \)) over the left to produce the observed right-hand traffic. The test sector \( S^{RF}_i \) is equally divided into four subsectors \( S_{S^{RF}_{sub}}^{RF} = \{ S^{RF-1}_i, S^{RF-2}_i, S^{RF-3}_i, S^{RF-4}_i \} \). Then, the direction \( u^{RF\_low, i} \in \{ u^{RF-1}_i, u^{RF-2}_i, u^{RF-3}_i, u^{RF-4}_i \} \) of the subsector with the lowest number of counterflow agents is selected as the movement direction (see figure 2). This process describes the counterflow avoidance behavior of a local leader.

Figure 3 shows a flowchart of the counterflow model. The rectangles denote different steps, the ellipses denote different behaviors, and the rhombuses represent the judgment conditions. The arrows indicate the direction of action flow. Figure 4 shows an example of the different calculation steps of the counterflow model. First, for the agent in purple, five agents in its evaluating sector are not in counterflow (\( n^{E\_nc}_{S^E_i} = 5 \neq 0 \)); hence, it is not a local leader. Second, vector \( c^E_i \) is obtained by evaluating the center
of the orange polygon surrounded by five vertices. Third, the total cost $T^*_i$ for each test direction is calculated. Fourth, sector $S^{RF}_i$ is selected as the total cost is the lowest in this sector ($T^{RF}_i = 7.2$). Finally, vector $c_i$ is obtained by evaluating the center of the orange polygon surrounded by four vertices in sector $S^{RF}_i$, and $c_i$ is selected as the movement direction.

2.1.2. Path planning model. The environment of the passenger ship is represented in the form of a graph $G (N, E)$ that contains all the locations (nodes; $N$) in the environment that agents may visit and all the connections (edges; $E$). In this model, the spacing between nodes is set to 0.4 m ($2\sqrt{2}/5$ m in the diagonal direction) [16]. Our path-planning model planned the shortest path from the current position of agent to an exit by employing the Dijkstra search algorithm [33]. In order to speed up the calculation, we ran the Dijkstra algorithm for each exit (root node) before a simulation and then stored the obtained shortest-path tree of each exit. The shortest path can be easily obtained by using the shortest-path tree. However, the Dijkstra search algorithm is not suitable for planning the shortest path from an agent to his/her lifejacket as the process will be memory- and time-intensive for considering thousands of lifejackets (the Dijkstra algorithm will have to be run hundreds of times and then hundreds of shortest-path trees will have to be stored). Thus, we used the widely known best-first search—$A^*$ search algorithm [34] to plan the shortest path from the agent to its lifejacket. We chose the straight-line distance between the agent and his/her lifejacket as our estimated cost function. More details of the path-planning model can be found in [16, 35].
2.1.3. Decision-making model. At each update, an agent evaluates his/her environment and selects the most desired high-level goal, which is broken down into subgoals that are subsequently satisfied. In turn, this process mirrors aspects of human deliberation in planning. In our model, an agent needs to wear a life jacket before starting to move to the assembly station. Figure 5 shows the process of decomposing goals. At the beginning of evacuation, an individual agent desires to evacuate and thus pursues the goal ‘evacuate’; this goal is broken down into ‘get a life jacket’ and ‘move to assembly station’. Then, the ‘get a life jacket’ goal can be further broken into ‘plan path’, ‘follow path’, and ‘don a life jacket’. The ‘follow path’ goal can be decomposed into a series of ‘move to node’ goals. Each of the ‘move to node’ goals contains a target node position \( p_i^0 \) in equation (11) on the shortest path, as calculated by the path-planning model. When an agent who does not wear a life jacket must return to his/her cabin, he/she will encounter others moving toward the assembly station, leading to counterflow. Passengers will then pursue the ‘avoid counterflow’ goal to dodge to the left or right.

Figure 6 presents a flow diagram of an agent pursuing certain goals in this model and their associated responses. The rectangles denote different goals, and the rhombuses represent the judgment conditions. The arrows indicate the direction of action flow. Note that the agent sometimes encounters congestion and cannot reach the target node in time. In this case, the agent needs to re-plan a path. When the agent encounters counterflow, he/she will dodge to the left or right to avoid the counterflow.

2.2. Preparation for simulations

The crowd movement model presented herein adopts our previous model [16]. We briefly introduce our previous model, which is a combination of the social force model [6] and group behavior [22]. This model assumes that each agent \( i \) is affected by desired force \( f_i^{de} \), the interaction force \( f_{iW} \) between pedestrian \( i \) and wall \( W \), the interaction force \( f_{ij} \) between pedestrians \( i \) and \( j \), and the resistance force \( f_{iS}^{f} \) generated by chair \( S \). The change in velocity \( v_i \) of an agent at time \( t \) can be calculated by

\[
\frac{dv_i}{dt} = f_i^{de} + \sum_W f_{iW} + \sum_{j \in B_i} f_{ij} + \sum_S f_{iS}^{f}
\]  

Figure 4. Example of the different calculation steps of the counterflow model.
where $m_i$ is the mass of agent $i$. $B_i$ denotes the set of agents within the neighborhood radius $R$ of agent $i$ according to

$$B_i = \{ j | j \in P, j \neq i, |p_i - p_j| < R \}.$$  

\hspace{1cm} (9)

The desired force $f^{de}_i$ reflects the behavior that agent $i$ attempts to move at a certain desired speed $v^0_i = |v^0_i|$ toward a target specified by the decision-making model. The desired force is given by

$$f^{de}_i = m_i \frac{v^0_i (t) - v_i (t)}{\tau_i}$$  

\hspace{1cm} (10)

where $\tau_i$ is the characteristic time needed for agent $i$ to change his/her current velocity to the desired velocity. The desired velocity is given by

$$v^0_i (t) = v^{\text{max}}_i \frac{|p^0_i (t) - p_i (t)|}{|p^0_i (t) - p_i (t)|}$$  

\hspace{1cm} (11)

where $v^{\text{max}}_i$ is the maximum walking speed of agent $i$. The target position $p^0_i (t)$ of agent $i$ is determined by the decision-making model. The details of the force $f_{iW}$, $f_{ij}^b$, and $f_{iS}^f$ can be found in the [16] or appendix A.
In order to combine with our counterflow model, we modify the desired force. If there is at least one other counterflow agent within the evaluating sector, the desired force can be modified as

$$f_{di} = m_i v_{i}^{\max} s_i(t)/|s_i(t)| - v_i(t)$$

(12)

where $s_i(t)$ is the moving direction of agent $i$ determined by the counterflow model ($s_i \in \{c_i, u_{i RF, low}\}$) at time $t$. This modification causes the agent to change its current moving direction toward the desired moving direction selected by the counterflow model.

Several parameters in our model are set as follows: $c^F = 0.1$, $c^{RF} = 0.2$, $c^R = 0.3$, $c^{LF} = 0.4$, $c^L = 0.5$, and $R^S = 1.5$ m. The default radius of sectors and the angle of the evaluating sector are extracted from [20], and the default values of other parameters are taken from the [6, 16, 21] (see appendix B). The angle (30 degrees) of the test sector is little than that (40 degrees) in [20], and it was found by trial-and-error to avoid unrealistic movement. This is because our model has more test sectors so that the angle of each sector should be smaller. The preference factors are used to deal with the situation where the basic costs of different test sectors are equal to zero. These preference factors can sort the total cost. For example, if $C_i^{RF} = C_i^R = 0$ ($T_i^{LF} = 0.5 > T_i^R = 0.3$), one could prefer the right over the left. We chose some ordered values (0.1, 0.2, 0.3, 0.4, and 0.5) for preference factors so as to endow the test directions with priorities (for instance, front preferred over right front, right front over right, right over left front). As basic cost is an angle in nature, its interval (0–170) can be intuitively deducted. The preference factors (below 0.5) exert little effect on the total cost unless basic cost is equal to zero. Furthermore, we can designate the preference factors with some different decimals of the same sequencing (e.g. $c^{RF} = 0$, $c^{RF} = 0.03$, $c^R = 0.07$, $c^{LF} = 0.09$, and $c^L = 0.2$), which can barely change the running outcome of this model. Note that the counterflow model can be modified to apply to countries with left-hand traffic by selecting the test sector $S_i^{LF}$ to divide for the local leader. In such case, the preference factors should

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Figure 7. Arrangement of International Maritime Organization (IMO) test 8—counterflow [1].
be modified to $c^F = 0.1$, $c^{RF} = 0.4$, $c^R = 0.5$, $c^{LF} = 0.2$, and $c^L = 0.3$. These parameter values are not necessarily optimal for counterflow, but they produce reasonable results.

All the simulations were run on a laptop with an Intel Core (TM) i7 3.7 GHz CPU, Nvidia GTX 1080 GPU, and 64 GB of memory. The model was developed using C++ with DirectX 12 SDK in a Microsoft Visual 2017 environment.

2.3. Simulations

To verify the proposed model, we conducted IMO test 8, which is a qualitative verification and is included in MSC.1/Circ. 1533 Annex 3 [1]. Figure 7 shows the arrangement. Two rooms connected via a corridor are used for calculating the time needed for 100 people in room 1 to move to room 2 as 0, 10, 50, and 100 persons simultaneously move from room 2 to room 1. The maximum walking speeds of the passengers are evenly distributed in the range 0.97–1.62 m s$^{-1}$, as stated in IMO MSC.1/Circ.1533 Annex 3 [1]. The expected result was that the recorded time will increase with the number of passengers.

For quantitative verification, we selected the experiment described by Zhang and Klingsch [32] for simulation. Figure 8 shows the arrangement of the bidirectional flow experiment. Pedestrians started from the waiting area and passed through a 4 m passage into the corridor. When a pedestrian arrived at the other entrance of the corridor, he/she left the corridor from the passage. The average free velocity of the pedestrians is $1.55 \pm 0.18$ m s$^{-1}$. They did not provide the distribution of the velocity. We adopted the uniform distribution of the velocity in our simulation. The authors classified bidirectional streams into stable separated lane (SSL) and dynamical multilane (DML) flows. According to the typical densities in the opposing streams, the balanced flow ratio (BFR) and unbalanced flow ratio (UFR) are introduced. The experiment was carried out 22 times, and we selected 12 experiments with BFR for simulation. The relevant parameters are shown in table 1.

As a study case, we conducted evacuation simulations on deck 5 of a passenger ship early in its early design stage to examine the evacuation procedures. The reason why we chose this deck for simulation was that this deck has a relatively complicated layout (including assembly stations, public area and cabins) and it is of representative significance (having a similar layout as: Deck 8 of P&O-Pacific, Deck 4 of Carnival Spirit, Deck 8 of P&O-Pacific Jewel, and Deck 8 of Sea Princess et al). The arrangement of deck 5 is illustrated in figure 9. The size of this deck is approximately 156 m × 31 m,
and it has 18 first-class cabins, 155 second-class cabins, one restaurant, and 2 assembly stations. Each cabin has a maximum capacity of two passengers and is equipped with two life jackets. The restaurant has a maximum capacity of 292 passengers, and it has four doors, 70 tables, and 292 chairs. Unlike in the traditional evacuation simulation, in our simulation, passengers had to collect their life jackets prior to moving to the assembly station. This deck can accommodate up to 637 passengers. Some passengers needed to return to the deck on which their cabins were located to find a life jacket under the full loading situation, which requires the simulation of other decks. In order to reduce the calculation load, we only consider the 346 passengers living on deck 5.

When the simulation began, passengers first needed to collect and don their life jackets. Some passengers who were outside their cabins at the beginning of the simulation had to move back to their cabins to collect their life jackets. In all cases, once the life jackets were collected and worn, passengers moved to the assembly station designated by the signboard at the door of their cabin. In general, passengers from on the port side gathered at assembly station A, while others gathered at assembly station B. Owing to the asymmetrical layout of the deck, more passengers lived on the port side. In the actual evacuation scheme, some of the passengers in the port side cabins (shown in orange, see figure 9) gather at assembly station B in order to balance the utilization of the two assembly stations. The maximum unhindered walking speeds are uniformly distributed in the range 0.97–1.62 m s⁻¹. We distributed all the 346 passengers in the living cabins and restaurant in different proportions (0:10, 1:9, 2:8, 3:7, 4:6, 5:5, 6:4, 7:3, 8:2, 9:1, and 10:0), and the passengers in each cabin were randomly distributed.

Table 1. Related parameters in experiments [32].

| Index | Name                     | $b_{cor}$ (m) | $b_1$ (m) | $b_2$ (m) | $N_l$ | $N_r$ |
|-------|--------------------------|---------------|------------|------------|-------|-------|
| 1     | BFR-SSL-360-050-050      | 3.60          | 0.50       | 0.50       | 57    | 61    |
| 2     | BFR-SSL-360-075-075      | 3.60          | 0.75       | 0.75       | 56    | 80    |
| 3     | BFR-SSL-360-090-090      | 3.60          | 0.90       | 0.90       | 109   | 105   |
| 4     | BFR-SSL-360-120-120      | 3.60          | 1.20       | 1.20       | 143   | 164   |
| 5     | BFR-SSL-360-160-160      | 3.60          | 1.60       | 1.60       | 143   | 166   |
| 6     | BFR-DML-360-050-050      | 3.60          | 0.50       | 0.50       | 56    | 74    |
| 7     | BFR-DML-360-075-075      | 3.60          | 0.75       | 0.75       | 62    | 65    |
| 8     | BFR-DML-360-090-090      | 3.60          | 0.90       | 0.90       | 110   | 102   |
| 9     | BFR-DML-360-120-120      | 3.60          | 1.20       | 1.20       | 115   | 106   |
| 10    | BFR-DML-360-160-160      | 3.60          | 1.60       | 1.60       | 140   | 166   |
| 11    | BFR-DML-360-200-200      | 3.60          | 2.00       | 2.00       | 143   | 166   |
| 12    | BFR-DML-360-250-250      | 3.60          | 2.50       | 2.50       | 141   | 163   |

Figure 9. Arrangement of deck 5 considered in the simulation.
The time that a passenger spends to free and don their life jacket was assumed to be uniformly distributed over the interval 5–10 s. These times were only optimistic estimates under the assumption that passengers are familiar with the procedure of freeing and donning their life jackets. In addition, we evaluated the evacuation times for each proportion and compared them with the simulations in which no life jackets were considered. Moreover, no additional pre-movement activities (e.g. collecting belongings) were simulated. We ran 50 simulations for each scenario.

3. Verification

3.1. Verification of the counterflow model through IMO test 8

Figure 10 presents snapshots of the simulation in which 50% of the total passengers are in counterflow. Table 2 lists the recorded time for each counterflow alternative and presents comparisons with results obtained using other commercial software. It was confirmed that the evacuation time increased with the increase in the number of passengers in room 2; however, the IMO did not offer quantitative evacuation times. There are differences in evacuation times obtained using different software. This discrepancy may be caused by the different computational models employed by the software.

In view of the differences in the results of commercial software, we compared the model with experiments completed in similar scenarios [41, 42]. Kretz et al [41] carried out a counterflow experiment in a corridor which differed slightly from IMO Test 8 in the layout. Two groups of people stood apart with a distance of 20 m in a 1.98 m-wide corridor. The main group contained 33 participants whereas the reverse group had varying numbers (0, 4, 17 and 34) of participants. The proportion of counterflow participants to all participants was the same as that in IMO Test 8. Table 3 lists the evacuation time in the simulation and makes a comparison with the experiment. We almost got identical result as the experiment in unidirectional flow. For bidirectional
For rigorous validation, more experimental data are still needed. Our model better matches the reality to some extent. The present model predicted time is longer than the experimental result but shorter than that generated by most commercial software. It means our model is more suitable to the scenes with dense population and short-range counterflow avoidance. In summary, it is clear that our model is 55.5% faster than the experiment.

### Table 2. Comparison of the evacuation times in this study and those obtained using commercial software for IMO test 8.

| Number of counterflow passengers | 0 (s)  | 10 (s) | 50 (s) | 100 (s) |
|----------------------------------|-------|-------|-------|---------|
| Pathfinder 2016 (steering) [36]  | 66.3  | 86.5  | 143.9 | 207.9   |
| Pathfinder 2016                  | 66.3  | 86.5  | 143.9 | 189.1   |
| (steering+SFPE) [36]             |       |       |       |         |
| Pathfinder 2016 (SFPE) [36]      | 29.9  | 30.7  | 31.3  | 31.8    |
| Evi [23]                         | 88.9  | 125.6 | 229.1 | 327.9   |
| FDS + Evac [37]                  | 50.0  | 75.0  | 106.9 | 136.1   |
| SIMPEV (cell-based) [23, 26]     | 84.6  | 93.2  | 137.1 | 216.1   |
| SIMPEV (velocity-based) [25]     | 83.2  | 90.8  | 129.4 | 201.4   |
| VELOS [38]                       | 108.5 | 238.9 | 349.9 | 434.4   |
| UNITY [39]                       | 82.3  | 108.1 | 224.3 | 277.7   |
| MassMotion [40]                  | 70.0  | 80.0  | 136.0 | 208.0   |
| The present model                | 55.5  | 84.7  | 134.3 | 170.8   |

### Table 3. Comparison of the evacuation times in this study and those in counterflow experiment.

| Percentage of counterflow participants | 0%  | 10% | 34% | 50% |
|---------------------------------------|-----|-----|-----|-----|
| Kretz et al [41]                     | 20.3| 21.6| 23.1| 26.2|
| The present model                     | 20.8| 24.3| 27.5| 34.7|
| Increment                             | 0.5 | 2.7 | 4.4 | 8.5 |

Flow, our result was 12.5%–32.4% slower than the experimental one as the proportion of counterflow participants increasing. A major reason behind such phenomenon is that agents can only react to the counterflow within 1.5 m, and thus, the 20 m empty part of the corridor is not exploited as well as in the experiment. It is infeasible to directly extend our model to such longer ranges; otherwise, it will lead to impractical phenomenon, namely the agents can only gather on the right side of corridor entrance. Besides, the number of participants in the experiment is far lower than that in IMO Test 8, and no walking speed is provided in the experiment. The range and the distribution of walking speed of our simulation are the same as that in IMO Test 8. Cao et al [42] carried out a counterflow experiment in a 10 m-long and 4 m-wide corridor. Altogether 736 participants were divided into two groups in the corridor (with the counterflow ratio being about 53.3%). The maximum walking speeds of the participants are in the range 1.22–1.68 m s\(^{-1}\) (uniform distribution was adopted in our simulation). The evacuation time predicted by our model (336.4 s) is 6.1% slower than that resulting from the experiment (317.0 s). It means our model is more suitable to the scenes with dense population and short-range counterflow avoidance. In summary, it is clear that our predicted time is longer than the experimental result but shorter than that generated by most commercial software. Our model better matches the reality to some extent. For rigorous validation, more experimental data are still needed.

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3.2. Experimental verification reported in literature

In the SSL flow experiment, Zhang and Klingsch did not specify the exit through which a participant left. The opposing flows were separated along the middle of the corridor. Stable lanes formed autonomously and immediately after the run started (see figure 11(a)). Figure 11(b) shows the pedestrian trajectories obtained from the simulation for SSL flow. When pedestrians encountered the counterflow in the model, they tended to dodge to the right; hence, they are more likely to select the exit on the right-hand side based on the shortest path. This expectation is consistent with the experimental observation. However, a few pedestrians selected the exit on their left-hand side. This is because that they were pushed toward the left side, and they then exited from the left side. In the DML flow experiment, pedestrians were assigned an exit based on a number given to them in advance (odd numbers select the left exit, and even numbers select the right one). The lanes are unstable and vary in time and space (see figure 11(c)). Figure 11(d) shows the pedestrian trajectories obtained from the DML flow simulation, and they agree with the results of the experiment. In addition, the trajectories are not as smooth as the ones obtained in the experiment because the direction of movement of pedestrians is decided according to the discrete grid points in the simulation.

Figure 11. Trajectories of pedestrians. Green lines represent the trajectories of pedestrians from the left, while the blue ones represent those of pedestrians from the right. (a) Stable separated lane (SSL) experiment [32], (b) SSL simulation, (c) dynamical multilane (DML) experiment [32], and (d) DML simulation.
One of the most important characteristics of the pedestrian dynamics is the fundamental diagram that shows the relationship between pedestrian flow and density. We used the Voronoi method \[32\] to analyze the flows quantitatively in the same manner as Zhang and Klingsch chose for the experiment. Figure 12 compares the fundamental diagrams among the experiment, Pathfinder, and our simulation. The density-velocity diagrams from the experiment, Pathfinder, and the proposed model (figures 12(a) and (c)) show that the pedestrian velocity decreases as pedestrian density increases. The density-specific flow diagrams from our simulation and the experiment (figures 12(b)
and (d)) show that the specific flow first increases as the pedestrian density increases and then stabilizes, however, the specific flow from Pathfinder first rises and then decreases (similar to unidirectional fundamental diagram \[32\]). The fundamental diagrams of the experiment and our simulation are almost in agreement. The maximum density according to our fundamental diagrams of SSL flow is slightly larger than the experiment value. For the same density, each value of fundamental diagrams of Pathfinder is smaller than that of other fundamental diagrams. In addition, Pathfinder has the largest maximum density in the rest of fundamental diagrams. This discrepancy may be caused by the different computational models and the input parameters. The two models share similarities in input parameters—the pedestrian radius of 0.25 m and the walking speed range of 1.37–1.73 m s\(^{-1}\). The difference is that when the density increases, Pathfinder uses the speed-density curve to reduce the walking speed, and the walking speed of our model is only affected by the interaction force. Furthermore, the speed-density curve is obtained from the unidirectional speed-density data, which is different from the bidirectional one. The bidirectional fundamental diagrams of Pathfinder are similar to the unidirectional ones.

4. Results of case study

Figure 13 presents snapshots of the simulation in which 50% of the total passengers were initially located in the restaurant \((t = 0\ s)\). At \(t = 76\ s\), most of the passengers in the restaurant have left the restaurant and met others wearing life jackets at the end of the corridor. Obvious bidirectional pedestrian flow and congestion can be observed here. At \(t = 241\ s\), most of the passengers have donned their life jacket and arrived at the assembly station.

Figure 14 presents evacuation times for different numbers of passengers in restaurant as a percentage of the total number of passengers. For the simulations without life jackets, the greater the proportion of passengers in the restaurant, the shorter is approximate evacuation time needed. This is because the restaurant is close to the assembly station, and it takes less time to evacuate passengers from here than from
the cabins. For the simulations with life jackets, as the proportion of passengers in the restaurant increases, the evacuation time also increases. When all the passengers are in the cabins, the evacuation time is almost the same for the two cases. This is because passengers can quickly don life jackets and do not need to return to the cabins; hence, the trajectories are almost identical. In addition, when considering life jackets, the variance of the evacuation time is large because of the increase in evacuation uncertainty caused by the passenger’s return to the cabin.

In actual situations, for example, some passengers have dinners in the restaurant, and the evacuation times vary considerably between the simulation of evacuation with life jackets and the traditional simulation (without life jackets), and the evacuation time is about 2.3–3.5 times that in the traditional simulation. In order to reduce the impact of wearing life jackets on evacuation time, we propose two optimized schemes. One scheme is to provide an extra life jacket under each chair in the restaurant (table 4, scenario 3). The other is to place all the life jackets in the assembly station (table 4, scenario 4).

Table 4 lists the simulation results for different life jacket positions when 50% of the total passengers are initially located in the restaurant. Scenario 1 represents evacuation without life jackets, and Scenario 2, evacuation with life jackets. The average walking
distance in Scenario 2 (100.3 m) is approximately twice that in Scenario 1 (48.3 m). The average congestion experienced by passengers in Scenario 2 (19.2 s) is almost twice that in Scenario 1 (9.4 s). Therefore, evacuation takes longer in Scenario 2 than in Scenario 1 mainly because the return of the passengers to the cabins leads to an increase in the average moving distance; the second reason is that this returning movement causes congestion. In Scenario 3, all the results are slightly greater than those in Scenario 1, and the evacuation time (121.6 s) is the shortest among the Scenario 2, 3, and 4. In Scenario 4, the evacuation time is reduced by approximately 31% in comparison with the evacuation time in Scenario 2, but the reduction is not as much as that in Scenario 3. A passenger wasted approximately 35% of their personal evacuation time held up in congestion. This congestion was caused mainly because passengers were forced to queue up to collect their life jackets at the assembly station.

A graphical comparison of the cumulative arrival curves for Scenario 1, 2, 3 and 4 are depicted in figure 15. The arrival curves for Scenario 1 and 2 are similar and steeper, indicating a higher exit rate, which reflect the fact that there is no counterflow in these scenarios. The first half of the arrival curves for Scenario 2 and 4 are similar, but the second half of the curve for Scenario 4 extends with a shallow gradient, indicating a lower exit rate during that period of time.

Density and time are important means of identifying congestion. When the density exceeds a critical value (3.5 person m$^{-2}$) for a given period of time, congestion occurs. Figure 16 shows the density plots of occupant density exceeding 3.5 person m$^{-2}$. In the figure, heavy congestion (red area) is observed in Scenario 2 and Scenario 4. In Scenario 2, the congestion is mainly concentrated at the intersection of corridors and is caused by the return of the passengers to the cabins. In Scenario 4, the congestion is mainly concentrated in the area where life jackets are stored in the assembly station and is caused by the queuing up of passengers to collect their life jackets.

Figure 17 shows space utilization over the entire evacuation time for each scenario. The greater the red area, the more times has a passenger stepped on this area. Figure 17 show that the corridor space in Scenario 2 is most utilized area, unlike in the other three scenarios. This is consistent with the fact that the average walking distance of Scenario 2 is significantly longer than that in the other scenarios (table 4). It could be expected that a congested area will have longer occupation time.

![Figure 15. Cumulative arrival times generated by a simulation run for scenarios 1, 2, 3 and 4.](https://doi.org/10.1088/1742-5468/aaaf10c)
expected, the congested areas seen in figure 16 have longer occupation times (shown in red) in Scenario 2 and Scenario 4. The restaurant space utilization is different between Scenario 1 and Scenario 2; however, the utilization is almost identical in Scenario 1 and Scenario 4. This is because the passengers in the restaurant in Scenario 2 are heading toward the exit closest to their living cabins, not the nearest exit to the assembly station. The passengers in Scenario 3 need to search for life jackets in the restaurant, so the space utilization of the restaurant is higher in this scenario than in the others.
Table 5 presents a summary of critical issues of Scenarios 1, 2, 3, and 4. In Scenario 3, an overhead is caused by the need for extra life jackets. This modified evacuation scheme is the best so far. In Scenario 4, storing all the life jackets together in the assembly station causes a waste of space and results in challenges for ship designers. This scheme relies on the crew to distribute life jackets, but the crew may be injured or absent without leave. Moreover, the centralized storage of life jackets would increase the risk of loss of life jackets. For example, in the event of a fire in the life jacket storage area, all the life jackets may be simultaneously unavailable. However, it is possible to
avoid inconvenience to passengers after wearing life jackets and further avoid injuries caused by inconvenient movements. The evacuation time can be reduced by increasing the number of distribution locations of life jackets. In Scenario 2, the evacuation time can also be reduced by broadening the corridors.

5. Conclusion

Most existing ship models are derived from building evacuation models, ignoring the behavioral aspects of wearing life jackets. We have developed an agent-based social force model that considers the collection and donning of life jacket, following behavior, and counterflow avoidance behavior. The present model meets all the requirements of IMO MSC.1/Circ. 1533 test 8. However, IMO did not provide a quantitative evacuation time. This test is only a qualitative verification, not enough to determine the pros and cons of the model. Therefore, the results of the model are compared with experimental data from two similar scenarios. For the experiment on 67 pedestrians, our results are 32.4% slower than the experimental one. For the experiments on 736 pedestrians, our results are only 6.1% slower than the experimental one. In addition, our model is verified by fundamental diagrams obtained in previous counterflow experiments. Our results show that this model can reproduce collective phenomena, such as DML and SSL, in pedestrian traffic.

For the specific layout of the ship in figure 9, the evacuation time of the simulations with life jackets is much longer than that without life jackets (up to 3 times) if some passengers are not in their cabin before the evacuation. The collection and donning of life jackets is an important factor that affects evacuation time. Therefore, this behavior should not be ignored when developing a passenger ship evacuation model.

This paper provides two optimized evacuation schemes for the ship in figure 9 to improve safety. One scheme is to provide an extra life jacket under each chair in the restaurant. However, this scheme will cause additional overhead because extra life jackets are needed. The other scheme is to place all the life jackets in the assembly station. This scheme can help avoid inconveniences to passengers after wearing life jackets and further avoid injuries that may be caused by inconvenient movements. However, this scheme will cause a waste of space and pose challenges to ship designers. By providing

| Scenario | Life jackets position | Advantage | Disadvantage |
|----------|-----------------------|-----------|--------------|
| 1        | No life jackets       | Simple calculation | Inconsistent with reality |
| 2        | Cabins                | Space saving | Long evacuation time |
| 3        | Cabins and restaurant | Effectively shortened evacuation time | Overhead |
| 4        | Assembly stations     | Avoid the inconvenience and injuries cause by moving with a life jacket | Space waste; increase risk of loss of life jackets; rely on the responsibility of the crew |

Table 5. Summary of critical issues of scenarios 1, 2, 3, and 4.
the detailed analysis of different schemes (e.g. evacuation times, cumulated density plots, and space utilization diagrams), our model can help designers make reasonable decisions in selecting evacuation schemes.

However, actual evacuation may be more complex than our simulation. In future work, we will experimentally investigate the time that a passenger spends to free and don their life jackets and the movement after wearing the life jacket. Moreover, the evacuation of multiple decks of ships also needs to be studied.

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Appendix A. Interaction forces and resistance force

The interaction force $f_{iW}$ between agent $i$ and wall $W$ comprises three parts: the repulsive interaction force $f_{iW}^r$ that maintains the agent a certain distance away from the wall $W$, the body force $f_{iW}^b$ that counteracts body compression and the sliding friction force $f_{iW}^s$ that impedes relative tangential motion if the agent touches the wall. The interaction force between the agent and the wall is formulated according to equations as follows:

$$f_{iW} = f_{iW}^r + f_{iW}^b + f_{iW}^s,$$  \hspace{1cm} (A.1)

$$f_{iW}^r = k_g \frac{(R - d_{iW})}{R - r_i} n_{iW},$$  \hspace{1cm} (A.2)

$$f_{iW}^b = k_b \exp \left( \frac{g (r_i - d_{iW})}{B} \right) n_{iW},$$  \hspace{1cm} (A.3)

$$f_{iW}^s = -k_s g (r_i - d_{iW}) (v_i \cdot t_{iW}) t_{iW},$$  \hspace{1cm} (A.4)

and

$$g(x) = \begin{cases} x & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \end{cases},$$

where $B$, $k_r$, $k_b$, and $k_s$ are constants, $r_i$ is the radius of agent $i$, $d_{iW}$ is the distance between agent $i$ and wall $W$, $R$ is the agent’s neighborhood radius of the agent, $n_{iW}$ denotes the normalised vector perpendicular to the wall $W$ and $t_{iW}$ is the direction tangential the wall $W$. It is worth noting that $f_{iW}^r$, $f_{iW}^b$, and $f_{iW}^s$ are derived from the social force model.
The interaction force $f_{ij}$ between agents $i$ and $j$ acting upon agent $i$ comprises five parts: the steering force of separation $f_{ij}^s$ that keeps an agent away from its neighbors, the steering force of cohesion $f_{ij}^c$ that keeps an agent close to the local group formed by his/her neighbors, the steering force of alignment $f_{ij}^a$ that matches the direction and speed of the agent’s neighbors, the body force $f_{ij}^b$ that counteracts body compression and the sliding friction force $f_{ij}^s$ that impedes relative tangential motion in case agents touch each other. The interaction force between two agents is formulated according to equations as follows:

$$f_{ij} = f_{ij}^s + f_{ij}^c + f_{ij}^a + f_{ij}^b + f_{ij}^s, \quad \text{(A.5)}$$

$$f_{ij}^s = k_{se} \frac{n_{ij} \cdot d_{ij}}{d_{ij}}, \quad \text{(A.6)}$$

$$f_{ij}^c = k_{co} \frac{p_j - p_i}{|B_i|}, \quad \text{(A.7)}$$

$$f_{ij}^a = k_{al} \frac{v_j - v_i}{|B_i|}, \quad \text{(A.8)}$$

$$f_{ij}^b = k_b \exp \left( \frac{g (r_i - d_{ij})}{B} \right) n_{ij}, \quad \text{(A.9)}$$

and

$$f_{ij}^s = k_s g (r_i - d_{ij}) \cdot v_{ti}, \quad \text{(A.10)}$$

where $d_{ij} = p_i - p_j$ is the distance between agent $i$ and $j$, $n_{ij} = (n_{ij}^1, n_{ij}^2) = (p_i - p_j)/d_{ij}$ is the normalised vector pointing from agent $j$ to $i$, $|B_i|$ is the number of members of set $B_i$, $k_{se}$, $k_{co}$, and $k_{al}$ are constants, $t_{ij} = (-n_{ij}^2, n_{ij}^1)$ is the normalised vector perpendicular to $n_{ij}$ and $\Delta v_{ij} = (v_j - v_i) \cdot t_{ij}$ is the tangential velocity difference. It is worth noting that $f_{ij}^s$, $f_{ij}^c$, and $f_{ij}^a$ are derived from the steering force model, whereas $f_{ij}^b$ and $f_{ij}^s$ are derived from the social force model.

The resistance force $f_{is}^r$ simulating the role played by stools in an evacuation. The resistance force $f_{is}^r$ from stool $S$ impeding the movement of agent $i$ is given by

$$f_{is}^r = - k_f \frac{g(r_i + r_{st}^S - d_{is})}{r_i + r_{st}^S} v_i, \quad \text{(A.11)}$$

where $k_f$ is a constant, $r_{st}^S$ is the approximate radius of stool $S$, $d_{is}$ is the distance between agent $i$ and stool $S$. 

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Appendix B. Defaults of the parameters

See table B1.

| Parameter | Default value | Unit | Description                                      | Source              |
|-----------|---------------|------|--------------------------------------------------|---------------------|
| $m$       | 80            | kg   | Passenger mass                                   | Literature [6, 21]  |
| $r$       | 0.25          | m    | Passenger radius                                 | Literature [6, 21]  |
| $\tau$    | 0.5           | s    | Characteristic time                              | Literature [6, 21]  |
| $k_r$     | 2000          | N    | Strength of repulse interaction force           | Literature [6, 21]  |
| $k_b$     | 120 000       | kg m$^{-2}$ | Strength of body force                         | Literature [6, 21]  |
| $k_a$     | 240 000       | kg m$^{-1}$ s$^{-1}$ | Strength of sliding friction force              | Literature [6, 21]  |
| $R$       | 1.0           | m    | Neighborhood radius                              | Literature [16]     |
| $k_{se}$  | 2000          | kg m$^{-2}$ s$^{-2}$ | Strength of separation force                    | Literature [16]     |
| $k_{co}$  | 400           | kg s$^{-2}$ | Strength of cohesion force                      | Literature [16]     |
| $k_{al}$  | 800           | kg s$^{-1}$ | Strength of alignment force                     | Literature [16]     |
| $k_f$     | 1500          | kg s$^{-1}$ | Strength of friction force from stools          | Literature [16]     |
| $B$       | 0.08          | —    | Growth factor of compression force               | Literature [6, 21]  |
| $c^L$     | 0.5           | —    | Preference factor for left test sector           | Simulation          |
| $c^{LF}$  | 0.4           | —    | Preference factor for left front test sector     | Simulation          |
| $c^R$     | 0.3           | —    | Preference factor for right test sector          | Simulation          |
| $c^{RF}$  | 0.2           | —    | Preference factor for right front test sector    | Simulation          |
| $c^F$     | 0.1           | —    | Preference factor for front test sector          | Simulation          |
| $R^S$     | 1.5           | m    | Radius of sectors                                | Literature [20]     |
## Appendix C. Nomenclature

See table C1.

| Notation | Description |
|----------|-------------|
| $U_i$    | The set of test vectors of agent $i$ |
| $u_{i}^L,u_{i}^{LF},u_{i}^{F},u_{i}^{RF},u_{i}^{R}$ | Left, left front, front, right front, and right test vectors of agent $i$ respectively |
| $u^*$    | Any vector in the set $U_i$ |
| $S_i$    | The set of test sectors of agent $i$ |
| $S_{i}^{L},S_{i}^{LF},S_{i}^{F},S_{i}^{RF},S_{i}^{R}$ | Left, left front, front, right front, and right test sectors of agent $i$ respectively |
| $S_{i}^{*}$ | Any sector in the set $S_i$ |
| $S_{E}$ | Evaluating sector of agent $i$ |
| $S_{E}^{*}$ | The set of other agents in the evaluating sector |
| $R_S$ | Radius of all the sectors |
| $P$ | The set of all agents |
| $C_{i}$ | Basic cost of the test sector $S_i$ |
| $C_{i}^{L},C_{i}^{LF},C_{i}^{F},C_{i}^{RF},C_{i}^{R}$ | Basic cost of test sectors $S_{i}^{L},S_{i}^{LF},S_{i}^{F},S_{i}^{RF},S_{i}^{R}$ respectively |
| $T_{i}$ | Total cost of the test sector $S_i$ |
| $T_{i}^{L},T_{i}^{LF},T_{i}^{F},T_{i}^{RF},T_{i}^{R}$ | Total cost of test sectors $S_{i}^{L},S_{i}^{LF},S_{i}^{F},S_{i}^{RF},S_{i}^{R}$ respectively |
| $c_{E}^{*}$ | Vector toward the center of mass of the agents in the evaluating sector $S_{i}^{E}$ who are not in counterflow |
| $n_{E,nc}^{*}$ | Number of non-counterflow agents in the evaluating sector $S_{i}^{E}$ |
| $n_{i}^{*c}$ | Number of counterflow agents in the test sector $S_{i}^{*}$ |
| $c_{E}^{L},c_{E}^{LF},c_{E}^{F},c_{E}^{RF},c_{E}^{R}$ | Preference factors for test sectors $S_{i}^{L},S_{i}^{LF},S_{i}^{F},S_{i}^{RF},S_{i}^{R}$ respectively |
| $S_{Se}$ | Selected test sector with the lowest total cost |
| $n_{Se,nc}^{*}$ | Number of non-counterflow agents in selected sector $S_{Se}$ |
| $c_{i}$ | Vector toward the center of mass of the non-counterflow agents in selected sector $S_{Se}$ |
| $S_{RF}^{1},S_{RF}^{2},S_{RF}^{3},S_{RF}^{4}$ | Subsectors of the test vector $S_{i}^{RF}$ |
| $S_{RF,sub}^{2}$ | The set of the subsectors of the test vector $S_{i}^{RF}$ |
| $u_{RF,low}$ | Direction of the subsector with the lowest number of counterflow agents |
| $v_{i}(t)$ | Velocity of agent $i$ |
| $v_{i}^{0}(t)$ | Desired velocity of agent $i$ |
| $v_{i}^{max}$ | Maximum walking speed of agent $i$ |
| $s_{i}(t)$ | Moving direction of agent $i$ selected by the counterflow model |
| $p_{i}(t)$ | Target position of agent $i$ determined by the decision-making model |
| $p_{i}^{0}(t)$ | Position of agent $i$ |
| $u_{i}^{0}$ | Unit vector of the desired velocity $v_{i}^{0}$ |
| $m_{i}$ | Mass of agent $i$ |
| $f_{i}^{se}$ | Desired force of agent $i$ |
| $f_{iW}$ | Interaction force between agent $i$ and wall $W$ |
| $f_{ij}$ | Interaction force between agent $i$ and $j$ |
| $f_{iS}$ | Resistance force generated by chair $S$ |
Table C1. (Continued)

| Notation | Description |
|----------|-------------|
| $f_{W}^{i}$ | Body force between agent $i$ and wall $W$ |
| $f_{W}^{j}$ | Sliding friction force between agent $i$ and wall $W$ |
| $f_{b}^{i}$ | Steering force of separation between agent $i$ and $j$ |
| $f_{c}^{i}$ | Steering force of cohesion between agent $i$ and $j$ |
| $f_{a}^{i}$ | Steering force of alignment between agent $i$ and $j$ |
| $f_{w}^{i}$ | Body force between agent $i$ and $j$ |
| $f_{s}^{ij}$ | Sliding friction force between agent $i$ and $j$ |
| $d_{W}$ | Distance between agent $i$ and wall $W$ |
| $n_{W}$ | Normalised vector perpendicular to the wall $W$ |
| $t_{W}$ | Direction tangential the wall $W$ |
| $d_{ij}$ | Distance between agent $i$ and $j$. |
| $n_{ij}$ | Normalised vector pointing from agent $j$ to $i$ |
| $|B_{i}|$ | Number of members of set $B_{i}$ |
| $t_{ij}$ | Normalised vector perpendicular to $n_{ij}$ |
| $\Delta v_{ji}$ | Tangential velocity difference between agent $i$ and $j$ |
| $d_{iS}$ | Distance between agent $i$ and stool $S$. |
| $r$ | Passenger radius |
| $\tau$ | Characteristic time |
| $k_{r}$ | Strength of repulse interaction force |
| $k_{b}$ | Strength of body force |
| $k_{s}$ | Strength of sliding friction force |
| $R$ | Neighborhood radius |
| $k_{se}$ | Strength of separation force |
| $k_{co}$ | Strength of cohesion force |
| $k_{al}$ | Strength of alignment force |
| $k_{f}$ | Strength of friction force from stools |
| $B$ | Growth factor of compression force |
| $R^{s}$ | Radius of sectors |

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