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REGULAR PAPER

Robot-Guided Crowd Evacuation in a Railway Hub Station in Case of Emergencies

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Abstract

The rapid and orderly evacuation of passengers at the railway hub station in case of emergencies is an important issue for railway safety and efficiency. In this paper, a robot-guided passenger evacuation method is proposed to help passengers search evacuation paths and avoid potential risks. The number and initial positions of robots are determined by using a k-means clustering approach. The exit assignment and evacuation paths of robots are calculated by using a hybrid bi-level optimization approach taking into account the cooperative mechanism between robots. Then, a robot-guided crowd evacuation dynamical model is built based on a modified social force model, in which a navigation force is introduced to influence the speed and direction of evacuees. A case study of a typical railway hub station is used to demonstrate the effectiveness of the proposed approach. The scenarios of the mall and platform are designed to verify the evacuation efficiency under different robot distribution schemes. The experimental results prove that setting up robots can effectively reduce evacuation time, and the utilization of exits is more balanced. The proposed optimal scheme shows the best performance in evacuation efficiency, including evacuation time and exit utilization rate, compared to the uniform distribution scheme and no robot scheme.

Keywords Robot guided crowd evacuation · Modified social force model · Railway hub station · Robot distribution · Cooperative mechanism · Emergencies

1 Introduction

As a dispersal center of passengers, the railway hub station usually has a complex internal structure and interchange paths, and poor connectivity to the outside community. Passengers have difficulty finding destinations and walking/evacuation paths under normal and emergent events. Emergency evacuation of passengers is an important part of public safety. In case of emergency in crowded places of stations, such as platforms, tunnels, and other places, it is easy to cause serious congestion and even trampling and casualty events. Therefore, evacuating the crowd efficiently and safely becomes the key to ensuring social security issues.

In recent years, the problem of passenger evacuation in railway stations has received wide attention and focus from researchers and managers. An in-depth understanding of how passenger flow is organized in the station and the evacuation behavior of passengers is conducive to improving the evacuation efficiency of railway stations in case of emergencies. At the same time, measures of setting evacuation guidance such as leader, signage, and robot, are also recognized as effective means of providing guidance information on paths and exits and reducing evacuation time and casualties [1]. The signage system can provide basic directional and routing information for passengers, as well as evacuation routes in emergency situations. Its effectiveness largely depends on the message conveyed by the sign, the legibility, interoperability, and height of the sign. However, the signs suffer from shortcomings such as easy to be ignored and unintuitive instructions. Static indication information is

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difficult to be accepted, understood and adopted by evacuees. Leaders, having access to more information than passengers, can provide more direct evacuation information to passengers and lead them along safe, less crowded paths. However, setting up leaders often means a higher cost on an ongoing basis and is difficult to adapt to scenarios that could cause harm to leaders, such as fires.

Previous researchers have proposed various models like social force (SF) model [2], cellular automaton (CA) model [3], agent-based model [4], discrete-time motion (DTM) model [5] to study robot-guided evacuation problems. The effect of robots on human behavior has also been carefully considered in the model. Garrell et al. [5, 6] proposed a multi-robots cooperative optimization methods to guide and regroup evacuees during guiding evacuation missions. A DTM model was introduced to address this problem with the goal of minimization of cost for guiding evacuees. Boukas et al. [3] studied the robot-guided crowd evacuation by using a cellular automaton model and a custom-made robotic platform, the evacuees were guided to a less crowded exit by using a mobile robot and the evacuation efficiency were improved significantly. Zhang and Guo [7] presented a distributed multi-robot guided crowd evacuation system for improving the evacuation efficiency in case of emergencies. A cooperative algorithm was designed to generate the optimal exit distribution scheme and enable exits to be used properly. Sakour and Hu [4] proposed an agent-based evacuation system to study robot-assisted crowd evacuation, the quad-rotors were used to provide a safe and less crowded path for evacuees. The crowd evacuation efficiency under two robot guidance strategies i.e., shepherding and handoff, was investigated by Nayyar and Wagner [8]. Zhang et al. [9] attempted to quantitatively explore the impact of a robot and its type on pedestrian dynamics through controlled human-robot crossing experiments, which provides effective support for modeling realistic robot-guided pedestrian behaviors. Kim et al. [10] designed a portable robot with high-temperature resistance for environmental perception and guiding crowd evacuation in fire scenarios.

The robot-assisted pedestrian regulation has been investigated in typical scenarios such as shopping mall [2], exit corridor [11], walkway [12] and L-shaped area [13]. Tang et al. [2] proposed a modified social force model to study robot-assisted crowd emergency evacuation taking the panic propagation into account, the optimal exit solution is generated by using an exit selection algorithm with the goal of minimizing evacuation time. Jiang et al. [12, 14] formulated the robot-assisted pedestrian optimization problem into an optimal control based on the social force model with embedded passive human-robot interaction relation. An adaptive dynamic programming-based learning approach was proposed to optimize the robot motion parameters and control the movement of pedestrians at the desired speed, and finally to optimize pedestrian flow and reduce the risk of crowd disasters. Wang et al. [13] proposed a deep reinforcement learning to solve the same problem with maximization of the pedestrian outflow in the scenario of an L-shaped area with a bottleneck. Robots' motion decisions were learned online through a CNN and a Q network.

Sakour and Hu [15] reviewed the crowd simulation methods from macroscopic and microscopic perspectives and analyzed the positive effect of autonomous robots on disaster evacuation and rescue missions. Liu et al. [16] formulated the robot-assisted crowd evacuation as an optimal control problem, and the distribution and command of robots were determined. A stochastic differential equation model was proposed to describe the motion of pedestrians taking into account the impact of robots. Bahamid et al. [17] reviewed and discussed the robots-guided evacuation systems equipped with advanced perceptual devices such as cameras and sensors. The mechanisms of trust of evacuees in robots and the factors affecting human-robot trust during crowd evacuation have also received attention from researchers [18].

Robinette et al. [19, 20] systematically investigated how to efficiently guide crowd evacuation through robots and the mechanisms of change in evacuees' trust in robots through experiments with a total of more than 2,000 people. Experiments in real and virtual scenarios were implemented to compare their differences in robot trust. Most human evacuees would trust a guidance robot that conveys understandable messaging and exhibits effective guidance behavior in emergency scenarios. Robinette et al. [21] identified possible negative effects of the robot on crowd evacuation when robots did not perform well through controlled non-emergency and emergency experiments in an interior area of buildings. Wagner [22] given a view that the robot-guided evacuation is used as a paradigm for human-robot interaction, and a series of approaches for developing robots and solving evacuation problems were proposed to obtain solutions. Therefore, ensuring that the guidance information provided by robots is accurate and reliable is a prerequisite and key to improving the efficiency of robot-guided evacuation.

The main contribution is summarized as follows. Firstly, the number and initial positions of robots are determined by using a k-means clustering approach. Secondly, the exit assignment and evacuation paths of robots are calculated by using a hybrid bi-level optimization approach. Then, a robot-guided crowd evacuation dynamical model is built based on a modified social force model, in which a navigation force is introduced to influence the speed and direction of evacuees. At last, a case study in a typical railway hub station is conducted to demonstrate the effectiveness of the proposed approach.

The remainder of this paper is organized as follows. Section 2 presents and formulates the robot-guided crowd evacuation problem in a railway hub station, the robot-guided crowd evacuation schemes, including initial distribution, exit assignment, and path planning of robots, are generated based on k-means clustering and multi-objective collaborative optimization algorithms. In Section 3, the modified social force model is built to model the crowd evacuation dynamics with the guidance of robots. A case study is conducted to study the effectiveness of robot-guided crowd evacuation schemes in Section 4. The conclusions are made in Section 5.

2 Description and Formulation of Robot-Guided Crowd Evacuation Problem

In the event of an emergency such as a power outage or fire in the platform of railway hub station, the passenger's visual field is reduced, which makes it difficult for passengers to find an exit and a suitable evacuation path. By adding a certain number of robots in suitable places, the efficiency of crowd evacuation can be greatly improved and the difficulty of way-finding reduced. The proper placement of the robots and their coverage for evacuees greatly determines the robots' guiding efficiency. In addition, the choice of evacuation paths and exits for robots and their followers also affects evacuation efficiency.

The robot-guided crowd evacuation problem is transformed into a problem of determining the initial location and number of robots and evacuation paths. The optimal distribution scheme is formulated by using the k-means clustering method. The evacuation paths are then determined by a Multi-objective cooperative coevolutionary algorithm. A real platform scenario of railway hub stations is chosen for studying guidance schemes and characteristics of robot-guided crowd evacuation. The number and positions of robots are determined by considering the cost of robots and the coverage of passengers. A k-means clustering-based robot distribution optimization algorithm is proposed to search the initial position of robots during evacuation.

2.1 Scenario Description and Assumptions

We take a typical railway hub station as an example to illustrate the formulation of robot-guided crowd evacuation scheme (Fig. 1). The physical space of railway platform is defined by $\Omega \in R^2$. It is divided into a set of smaller grids with the size of $l * l$. The red lines represent the exits/entrances ($g = 1, 2, \cdots, G$). The blue blocks represent obstacles that cannot be penetrated, which are defined by areas ($m = 1, 2, \cdots, M$). The red dots ($r = 1, 2, \cdots, N_{rob}$) and black dots ($p = 1, 2, \cdots, N_{pas}$) correspond to the robots and passengers, respectively.

We make some reasonable assumptions in order to facilitate and simplify the problem formulation.

1) The robot always gives the right instructions, and the passenger always trusts the robot he/she chooses to follow.
2) There is no conflict in evacuation instructions given by various robots during the evacuation process.
3) The states of robots, i.e., position, linear velocity, and angular velocity, are completely controlled by the Central Control Room of railway hub stations.

2.2 Robots' Initial Distribution Optimization

A robots' initial distribution scheme is generated to determine the number and initial positions of robots in the platform of railway hub stations. The following fitness function is designed to evaluate the distribution scheme by trading off the cost of robots and coverage of passengers.

$$Fit = \frac{1}{\omega_r \cdot N_{rob} + \omega_c \cdot C_r} \tag{1}$$

where ω_r and ω_c are the wights of cost and coverage, respectively. C_r corresponding to the coverage of passenger, which is defined as follows:

$$C_r = \frac{N_{pas}}{N_c} \tag{2}$$

where N_{pas} is the total number of passengers on the platform at the beginning of the evacuation. N_c is the sum of the number of passengers guided by robots, which is calculated by the following equation.

$$N_c = \sum_{i=1}^{N_{pas}} IC_i \tag{3}$$

where IC_i is a binary variable, its value is 1 if passenger i is guided by a robot, and 0 otherwise. It is defined as shown in Equation 4. The schematic of coverage of passengers is shown in Fig. 2.

$$\underset{i \in g_r}{IC_i} = \begin{cases} 1 & d_{ir} \le r_{ro} \\ 0 & \texttt{otherwise} \end{cases} \tag{4}$$

where r_{ro} is the radius of influence of robot r. g_r represents the set of elements of cluster r. $d_{ir} = \sqrt{(x_r - x_i)^2 + (y_r - y_i)^2}$, (x_i, y_i) and (x_r, y_r) represent the coordinates of passenger i and robot r, respectively.

The initial positions of robots are obtained by using the k-means clustering method taking into account the passengers' distribution and the coverage of evacuees. The

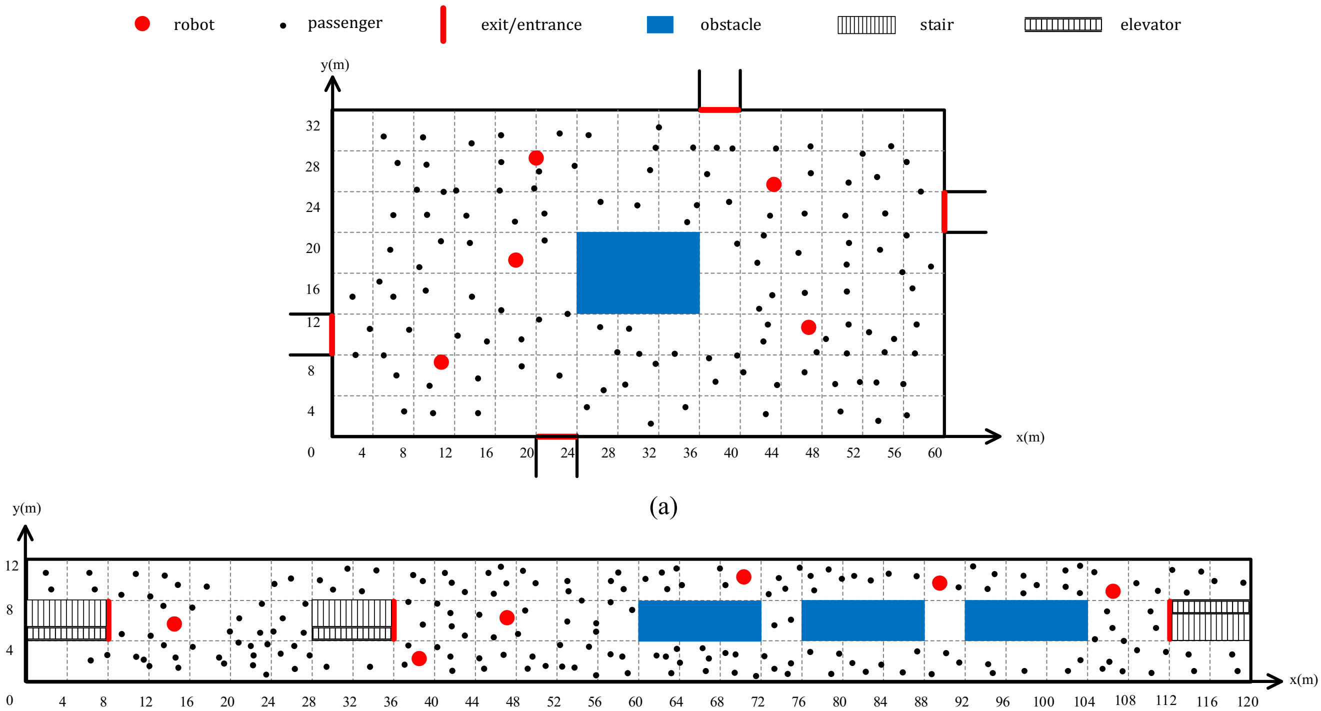


Fig. 1 The geometry of two typical scenarios at railway hub stations: (**a**) hall, and (**b**) platform

flowchart of the k-means clustering-based robot position optimization algorithm is shown in Fig. 3. The procedure of this algorithm can be summarized as follows:

Step 1 Initialization: inputting the geometry configuration of platform scenario, the initial distribution of passengers, and the initial number of clusters $k = 1,\ k \in [1, K]$;

Step 2 Increasing the number of clusters $k = k + 1$;

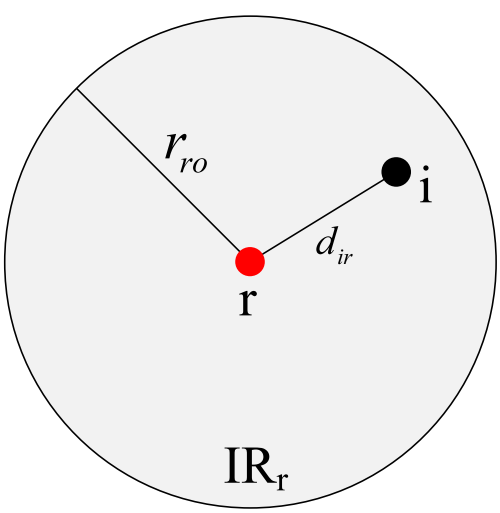


Fig. 2 The schematic of coverage of passengers

Step 3 Calculating the initial positions of robots (centroid) by using a k-means clustering method for a given number of clusters;

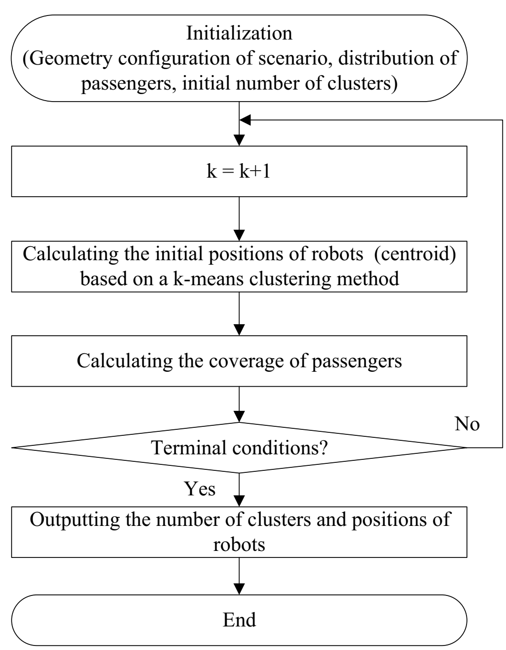


Fig. 3 The flowchart of k-means clustering based robot position optimization algorithm

Step 4 Calculating the coverage of passengers according to the Equation 4;

Step 5 Termination criterion: If the number of clusters reaches the maximum, or the values of the fitness function (Equation 1) for three successive iterations are no more decline, it is considered to converge to the optimal value and iteration process is terminated. Otherwise, skip to Step 2;

Step 6 Outputting the number of clusters and positions of robots.

2.3 Exit Assignment and Path Planning for Robots

After the initial positions and the number of robots are given, it is necessary to further assign exit and evacuation paths to them with certain objectives. Considering the real-time requirements and huge solution space of the exit assignment and path planning problem, we propose a hybrid bi-level approach to search for the optimal solution. The schematic of the solution procedure is described in Fig. 4. The upper level is used to solve robots' exit assignment problems, and the lower level is used to solve robots' path planning problems.

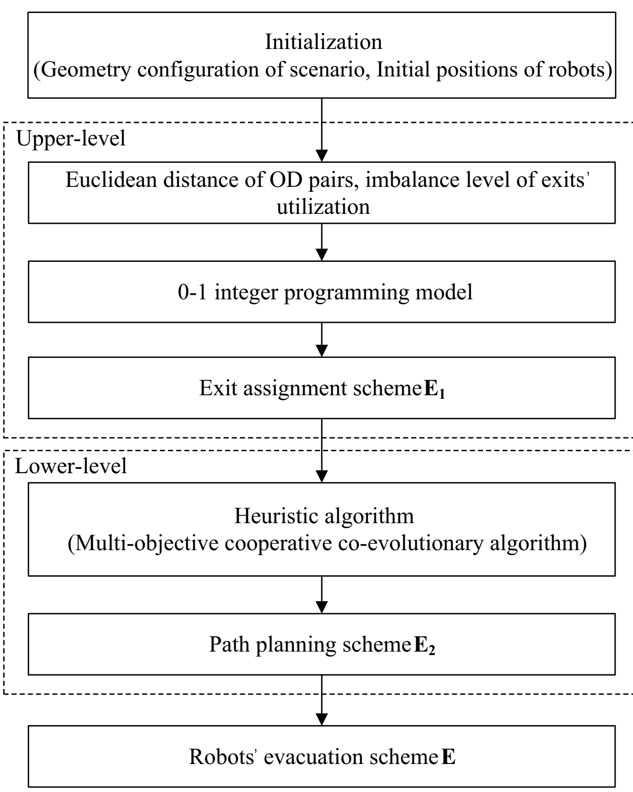


Fig. 4 Schematic of the solution procedure of the exit assignment and path planning scheme

2.3.1 Upper Level Exit Assignment

The initial position of robots is an $N_{rob} * 2$ dimensional matrix, which is denoted as $\mathbf{S} = [\mathbf{s}_1, \mathbf{s}_2, \cdots, \mathbf{s}_r, \cdots, \mathbf{s}_{N_{rob}}]'$, where $\mathbf{s}_r = (x_r^o, y_r^o)$. The decision variable of exit assignment is defined as $\mathbf{X}$, which is an $N_{rob} * N_{goal}$ dimensional matrix.

$$\mathbf{X} = \begin{bmatrix} \chi_{1,1} & \cdots & \chi_{1,N_{goal}} \\ \vdots & \ddots & \vdots \\ \chi_{N_{rob},1} & \cdots & \chi_{N_{rob},N_{goal}} \end{bmatrix}_{N_{rob} \times N_{goal}} \tag{5}$$

where $\chi_{r,g}$ is a binary variable, its value is 1 if robot r is assigned to exit g, and 0 for otherwise.

A bi-objective optimization model is built to determine the exit assignment scheme taking into account the path length and exit balancing.

$$H(\mathbf{X}) = \min\,[h_1(\mathbf{X}), h_2(\mathbf{X})] \tag{6}$$

$$s.t. \quad \sum_{g=1}^{N_{goal}} \chi_{r,g} = 1, \ \texttt{for}\ \forall r \in \{1, 2, \cdots, N_{rob}\} \tag{7}$$

$$\chi_{r,g} \in \{0, 1\} \tag{8}$$

where $h_1(\mathbf{X})$ and $h_2(\mathbf{X})$ represent the sum of Euclidean distance between the initial position and the destination and the imbalance level of exit utilization, respectively.

The $h_1(\mathbf{X})$ is defined as follow:

$$h_1(\mathbf{X}) = \sum_{r=1}^{N_{rob}} \sum_{g=1}^{N_{goal}} \chi_{r,g} \cdot d_{rg} \tag{9}$$

where d_{rg} represent the Euclidean distance between the robot's initial position and its destination.

The $h_2(\mathbf{X})$ is defined as follow:

$$h_2(\mathbf{X}) = \sum_{g=1}^{N_{goal}} \left(\frac{\left| \sum_{r=1}^{N_{rob}} \chi_{r,g} \cdot N_r^p - Ave^p \right|}{Ave^p} \right) \tag{10}$$

It reflects the degree of imbalance in the utilization rate of each exit during the crowd evacuation process under the guidance of robots. Ave^p represents the average number of evacuated passengers per exit, i.e., $Ave^p = \frac{N_{pas}}{N_{goal}}$. N_r^p denotes the number of passengers who choose to follow robot r for evacuation.

Constraint (7) indicates that each robot must be assigned an exit. Constraint (8) indicates the value of decision variable is 1 or 0. The $h_1(\mathbf{X})$ and $h_2(\mathbf{X})$ are normalized and their weights depend on the decision maker's preference. If the weight of $h_1(\mathbf{X})$ is 1, it degenerates to the shortest distance exit assignment scheme. If the weight of $h_2(\mathbf{X})$ is 1, it is the absolute mean exit assignment scheme. The above exit assignment problem is a typical 0-1 integer programming problem. It can be solved by using LINGO software.

2.3.2 Lower Level Path Planning

The initial position and destination of robot $r \in \{1, 2, \cdots, N_{rob}\}$ are $s_r = (x_r^o, y_r^o)$ and $g_r = (x_r^g, y_r^g)$, respectively. The decision variables of path planning for all robots are denoted as a matrix $\mathbf{P} = [\mathbf{P}_1, \cdots, \mathbf{P}_r, \cdots, \mathbf{P}_{N_{rob}}]$. The path of robot r is denoted as $\mathbf{P}_r = \{p_1, \cdots, p_j, \cdots, p_{l_r}\}$, where $p_1 = s_r$, $p_{l_r} = g_r$. After the initial positions and destinations of robots are given, a multi-objective optimization model is built to determine their evacuation paths.

$$F(\mathbf{P}^*) = \min\,[f_1(\mathbf{P}^*), f_2(\mathbf{P}^*), f_3(\mathbf{P}^*)] \tag{11}$$

where $f_1(\mathbf{P})$, $f_2(\mathbf{P})$, $f_3(\mathbf{P})$ represent the sum of the path lengths, smoothness, and safety performance, respectively.

The $f_1(\mathbf{P})$ is defined as follow:

$$f_1(\mathbf{P}) = \max_{r=1}^{N_{rob}} \{\mathtt{Len}(\mathbf{P}_r)\} + N_1 \cdot \eta_1 \tag{12}$$

where $\mathtt{Len}(\mathbf{P}_r)$ represents the path length of robot r, which is defined as $\mathtt{Len}(\mathbf{P}_r) = \sum_{j=1}^{l_r-1} \sqrt{(x_r^{j+1} - x_r^j)^2 + (y_r^{j+1} - y_r^j)^2}$. N_1 is the number of unfeasible segments in path $\mathbf{P}_r$. η_1 is a positive integer.

The $f_2(\mathbf{P})$ is defined as follow:

$$f_2(\mathbf{P}) = \sum_{r=1}^{N_{rob}} \mathtt{Smo}(\mathbf{P}_r) \tag{13}$$

where $\mathtt{Smo}(\mathbf{P}_r)$ represents the smoothness of the path of robot r, which is defined as $\mathtt{Smo}(\mathbf{P}_r) = \frac{\sum_{k=1}^{N_t} \cos\varphi_k}{N_t}$. N_t is the number of inflection points of the entire path of robot r and $\cos\varphi_k$ is the cosine of the $k\ th$ corner.

The $f_3(\mathbf{P})$ is defined as follow:

$$f_3(\mathbf{P}) = \max_{r=1}^{N_{rob}} \{\mathtt{Saf}(\mathbf{P}_r)\} \tag{14}$$

where $\mathtt{Saf}(\mathbf{P}_r)$ represents the safety performance of the path of robot r. When the path $\mathbf{P}_r$ is feasible, it is defined as $\mathtt{Saf}(\mathbf{P}_r) = \frac{1}{d_{\min}^o}$. $d_{\min}^o$ denotes the shortest distance between robot r and all obstacles and other robots during its motion process. Otherwise, $\mathbf{P}_r$ is defined as $N_1 \cdot \eta_3$, where η_3 is a positive integer.

We use a multi-objective cooperative co-evolutionary algorithm [23] to search the optimal paths for robots. The algorithm uses the Pareto dominance concept to extend the single-objective cooperative co-evolutionary model to solve multi-objective optimization problems. An external set of limited capacity is set to store the non-dominated solutions searched during the evolutionary process and make them participate in each generation to form the parental subpopulation of the new generation. Thus, starting from generation 2, the parents of the subpopulation contain the elite individuals retained by the external set. Each individual to be evaluated in the subpopulation of children generated by the reproduction operation will cooperate to generate the complete solution from randomly selected individuals from the parents of the remaining subpopulation (the purpose of random selection is to increase the diversity of the searched candidate solutions) and determine whether the solution should be updated for the external set based on the concept of Pareto domination: if no solution exists in the external set that dominates or is equal to the solution, the solution is added to the external set and all solutions in the external set that are dominated by the solution are removed; otherwise, the newly generated solution is discarded. The procedure of multi-robots' path planning is as follows:

Step 1 Let evolutionary generation $e = 1$, randomly generate N_r initial parent-subpopulations $Parpop_i(r)$ with the size N_c, and set an empty external set $\mathbf{A}$. Each chromosome in the subpopulation represents a path of robot r, encoded in floating point numbers with the following structure:

$$Parpop_i(r) = [(x_r^1, y_r^1), \cdots, (x_r^j, y_r^j), \cdots, (x_r^{lr}, y_r^{lr})] \tag{15}$$

Step 2 Perform evolutionary operations, i.e., crossover, mutation, deletion, repair, and smooth, on each parent subpopulation in turn to generate N_r child subpopulations $Childpop_i(r)$.

Step 3 Let each individual in the $Childpop_i(r)$ cooperate with the parent $Parpop_j(r)$ of the rest of the subpopulation, in turn, to generate a complete solution, calculate the value of the multi-objective function of the solution, and determine whether the solution should be updated or discarded for the external set $\mathbf{A}$ until all individuals in the subpopulation of all children have been processed.

Step 4 If the number of solutions in the external set $\mathbf{A}$ exceeds its maximum capacity M, a reduction operation is performed on it to remove those solutions that have the nearest neighbors (the shortest distance to the remaining solutions).

Step 5 If $|\mathbf{A}| \leq N$ ($|\cdot|$ denotes the number of elements in the set), then $N-|\mathbf{A}|$ individuals are randomly selected from each offspring subpopulation $Childpop_i(r)$, respectively, and they are combined with the corresponding components of all solutions in $\mathbf{A}$ to form a new generation of parent subpopulation $Childpop_{i+1}(r)$, otherwise, if $|A| > N_c$, then N_c solutions are randomly selected from $\mathbf{A}$ and their components are combined to form a new generation of parent subpopulation.

Step 6 If the termination condition is satisfied, then the external set A is output as the final found non-dominated soluion set and the algorithm terminates, otherwise, $e = e + 1$ and go to step 2.

3 Modeling of Crowd Evacuation Dynamics with the Guidance of Robots

3.1 Robot Kinematic Model

In this study, the two-wheeled differential drive robot is chosen to guide pedestrian evacuation in case of emergencies. The differential drive is a two-wheeled drive system with independent actuators for each wheel. The illustration of the two-wheeled differential drive robot kinematic model is shown in Fig. 5. v_l and v_r are the speeds of the left wheel and right wheel of the robot, respectively. d_{wb} denotes the diameter of the outer circle of the robot, r_c denotes the steering radius of the center point of the robot. $[v_c,\ \ \omega]^T$ describes the speed of the center point (red circle), where v_c is the linear velocity, and ω is the angular velocity. The blue curve is the trajectory of the robot. ICR is an abbreviation for the instantaneous center of rotation, which represents the point that the rigid body has only rotational motion around it.

An inverse kinematic model is designed by direct controlling of the two-wheeled differential drive method.

$$\begin{bmatrix} v_r \\ v_l \end{bmatrix} = \begin{bmatrix} 1 & \frac{d_{wb}}{2} \\ 1 & -\frac{d_{wb}}{2} \end{bmatrix} \begin{bmatrix} v_c \\ \omega \end{bmatrix} \tag{16}$$

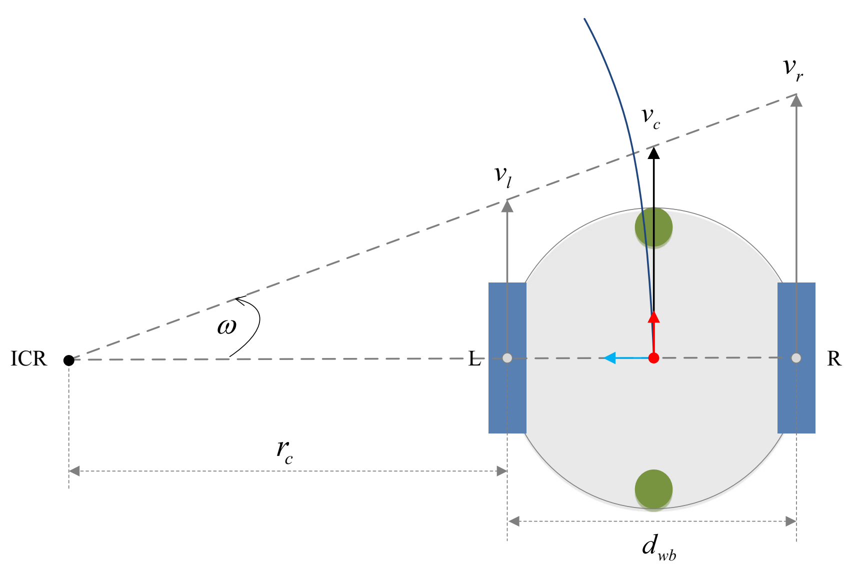
If the center of a robot is controlled to move at a preset speed (v_c, ω), then the theoretical speed of the two drive wheels is calculated by Eq. 16, and then the PID algorithm is used to control the precise rotation of the drive wheels.

During the crowd evacuation in case of emergencies, the linear velocity v_c is determined by the speed of the passengers following it. The angular velocity ω is determined by the evacuation path of the robot.

3.2 Robot-Guided Crowd Evacuation Model

In this paper, the effects of robot guidance on passenger dynamics are formulated based on the social force model [24]. During the evacuation passengers will choose to follow the robot or their neighbors depending on their surroundings. When passengers do not know the location of the exits, they will choose to follow the robot or their neighbors depending on the surroundings during the evacuation process. The presence of robots affects not only the desired direction but also the movement velocity of the passenger. The diagram of the modified social force model for robot-guided passenger movement is shown in Fig. 6. The circular vision field (VF) with a certain radius r_{vf} is considered in this model ([25–27]). d_{ij}, d_{iw}, and d_{ir} represent the

Fig. 5 Illustration of the two-wheeled differential drive robot kinematic model



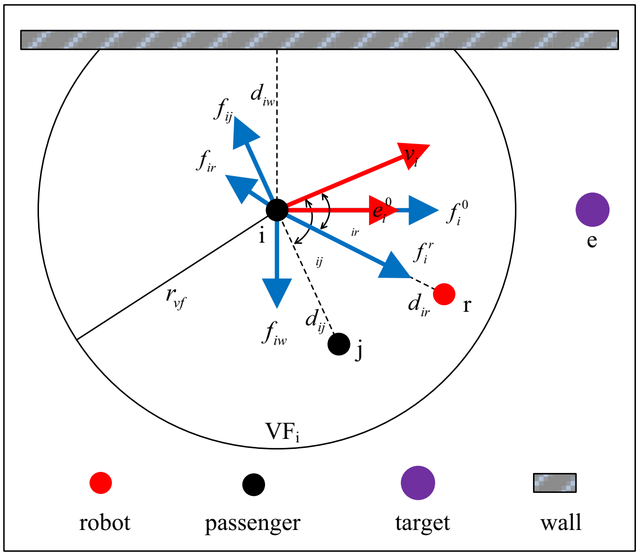


Fig. 6 Illustration of the decision maker interacting with environments under the effect of robot

distances between the passenger i and passenger j, obstacle w, and robot r, respectively.

The modified social force model for passenger movement is formulated as follows:

$$m_i \frac{d\boldsymbol{v}_i}{dt} = \boldsymbol{f}_i^0 + \sum_{j \in VF_i} \boldsymbol{f}_{ij} + \sum_{w \in VF_i} \boldsymbol{f}_{iw} + \sum_{r \in VF_i} \boldsymbol{f}_{ir} + \boldsymbol{f}_i^r, \tag{17}$$

where VF_i represents the visual field of passenger i. $\boldsymbol{f}_i^0$ represents the desired force of passenger i, which reflects the speed that the passenger wants to achieve. $\boldsymbol{f}_{ij}$, $\boldsymbol{f}_{iw}$, and $\boldsymbol{f}_{ir}$ correspond to the 'interaction force' between passenger i and passenger j, passenger i and wall w, and passenger i and robot r, respectively.

The desired force $\boldsymbol{f}_i^0$ is expressed by the following equation:

$$\boldsymbol{f}_i^0 = m_i \frac{v_i^0(t)\boldsymbol{e}_i^0 - \boldsymbol{v}_i(t)}{\tau_i}, \tag{18}$$

where $\boldsymbol{e}_i^0(t)$ corresponds to the desired direction of passenger i, which is in accordance with the direction of guidance's instruction, $v_i^0(t)$ and $\boldsymbol{v}_i$ represent the desired speed and actual velocity of passenger i, τ_i is the relaxation time [24].

The definitions of $\boldsymbol{f}_{ij}$ and $\boldsymbol{f}_{iw}$ are consistent with those presented in the Ref. [25]. The effect of the visual field in socio-psychological force is also considered in this model.

$$\begin{aligned} \boldsymbol{f}_{ij} = \; & A_i \cdot \exp[(r_{ij} - d_{ij})/B_i] \cdot \boldsymbol{n}_{ij} \cdot \\ & \times \left(\lambda_i + (1-\lambda_i)\frac{1+\cos(\varphi_{ij})}{2}\right) + \\ & k \cdot g(r_{ij} - d_{ij}) \cdot \boldsymbol{n}_{ij} + \kappa \cdot g(r_{ij} - d_{ij}) \cdot \Delta v_{ji}^t \cdot \boldsymbol{t}_{ij} \end{aligned} \tag{19}$$

where λ_i is a constant that takes values in the range 0-1. It determines that passengers in front of the visual field bring a greater impact than those behind. The angle φ_{ij} is defined as follows: $\cos\varphi_{ij}(t) = -\boldsymbol{n}_{ij}(t) \cdot \boldsymbol{e}_i(t)$.

$$\begin{aligned} \boldsymbol{f}_{iw} = \; & A_i \cdot \exp[(r_i - d_{iw})/B_i] \cdot \boldsymbol{n}_{iw} \\ & + k \cdot g(r_i - d_{iw}) \cdot \boldsymbol{n}_{iw} + \\ & \kappa \cdot g(r_i - d_{iw}) \cdot \Delta v_{wi}^t \cdot \boldsymbol{t}_{iw} \end{aligned} \tag{20}$$

The interaction force of $\boldsymbol{f}_{ir}$ between passenger i and robot r is similar with that of $\boldsymbol{f}_{ij}$. The definition of other parameters is the same as that in Ref. [28].

We introduce the navigation force $\boldsymbol{f}_i^r$ to quantify the effect of the robot guidance on the movement of passenger i. It reflects the tendency that the passenger try to move toward the robot. During the evacuation process, the navigation force is generated when passenger i chooses to follow robot r. The navigation force $\boldsymbol{f}_i^r$ is formulated as follows:

$$\boldsymbol{f}_i^r = \alpha_i \cdot m_i \cdot \left[-b_1 \frac{\boldsymbol{x}_i(t) - \boldsymbol{x}_r(t)}{\tau_i^2} - b_2 \frac{\boldsymbol{v}_i(t) - \boldsymbol{v}_r(t)}{\tau_i} \right] \tag{21}$$

where α_i is a binary variable, its value is 1 if the follower i can get the robot's information, and 0 for otherwise. b_1 and b_2 are coefficients, which reflect the weights of navigational feedback. $\boldsymbol{x}_i(t)$ and $\boldsymbol{x}_r(t)$ are the positions of follower i and robot r respectively at time t. $\boldsymbol{v}_r(t)$ is the speed of robot r at time t.

The environment of railway hub stations is complex and changeable in case of emergency. According to the distributions of robots, passengers, obstacles, and exits, the flowchart of passenger's decision process under the influence of robots is shown in Fig. 7.

Based on the flowchart shown in Fig. 7, the rules for determining the desired direction of a passenger i is defined as follows:

$$\boldsymbol{e}_i^0 = \begin{cases} \boldsymbol{e}_{exit}, & \text{exit} \\ \boldsymbol{n}_{ir}, & \text{robot} \\ \mathrm{Norm}[(1-p_i) \cdot \boldsymbol{e}_i + p_i \left\langle \boldsymbol{e}_j^0(t) \right\rangle_i], & \text{neighbours} \\ \mathrm{Rand}(\boldsymbol{n}), & \text{nothing} \end{cases} \tag{22}$$

From the passenger evacuation dynamics model described in Equation. 17, it is clear that when passengers choose to follow the robot for evacuation, they are subjected to navigational forces (Equation 21) and thus change their movement speed, while the desired direction changes, i.e., following the path of the guiding robot.

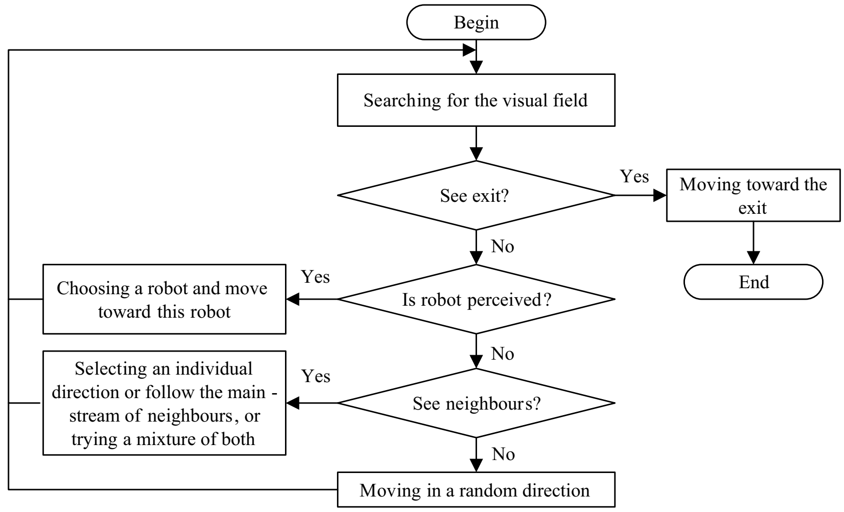


Fig. 7 Flowchart of passenger's decision process for the desired direction under the influence of guidance

The optimization problem considered in Section 2 is to obtain the optimal initial distribution of robots and their exits and evacuation paths. Among them, the robot cost and coverage of passengers are examined in the initial distribution optimization, which is to maximize the robot guidance efficiency and lead as many passengers as possible for evacuation with as few robots as possible. In the optimization of exit assignment and path planning, factors such as the length of the evacuation path and utilization of each exit (degree of imbalance) are taken into account in order to reach the exits as quickly as possible and to make each exit is used rationally.

4 Case Study

A case study of a typical Beijing railway hub station is used to demonstrate the effectiveness and feasibility of the proposed approach. The typical scenarios of the mall and platform, as shown in Fig. 1, are chosen to simulate the crowd evacuation dynamics with the guidance of robots. The robot-guided evacuation scheme is obtained according to the method proposed above, which is noted as Opt_Dist. We also design the uniform distribution (Uni_Dist) and no robot guidance (No_Robot) as comparison schemes. For the Uni_Dist scheme, a given number of robots are uniformly distributed in the hall. The number of robots is consistent with that in the Opt_Dist scheme.

The robot kinematic model and passenger evacuation model are adopted to simulate the dynamics of robots and evacuees respectively, during evacuation in case of emergencies.

General parameters of the scenarios, the modified social force models, and algorithms are shown in Table 1. For each follower, the weights $b_1 = 0.05$ and $b_2 = 0.05$ are same as that in Refs. [29] and [27].

The geometry of the mall is shown in Fig. 1a. There are four 4-meter wide entrances/exits on four sides of the mall, which are recorded as A, B, C, and D starting from the west in a clockwise direction. Its area is 1920 square meters. It has an obstacle with the size of 8 $m * 4$ m in the middle of the mall. The scenario of a smoke-filled mall is designed to validate the proposed strategy. 300 passengers are randomly distributed in the station with randomly given initial directions and speeds. The radius of the visual field r_{vf} is set to 10 m in this paper. The range of visual field of these passengers is affected by the smoke. The Opt_Dist scheme is generated by using the method proposed in Section 3. Simulation experiments under the three schemes are performed.

The snapshots of the robot-guided crowd evacuation with the Opt_Dist scheme at a mall of railway hub station at different time steps are shown in Fig. 8. At the beginning of the evacuation, 300 passengers are randomly distributed in

Table 1 General parameters of the scenario and the modified social force model

Symbol	Meaning	Value
m_i	Passenger mass	65 kg
r_i	Passenger radius	0.3 m
τ_i	Characteristic time	0.5 s
A_i	Avoidance force intensity	2000 N
B_i	Avoidance coefficient	0.08 m
κ	Coefficient of sliding friction	2.4×10^5 $kgm^{-1}s^{-1}$
k	Body compression coefficient	1.2×10^5 kgs^{-2}
λ_i	Non-isotropic influence of vision field	0.3

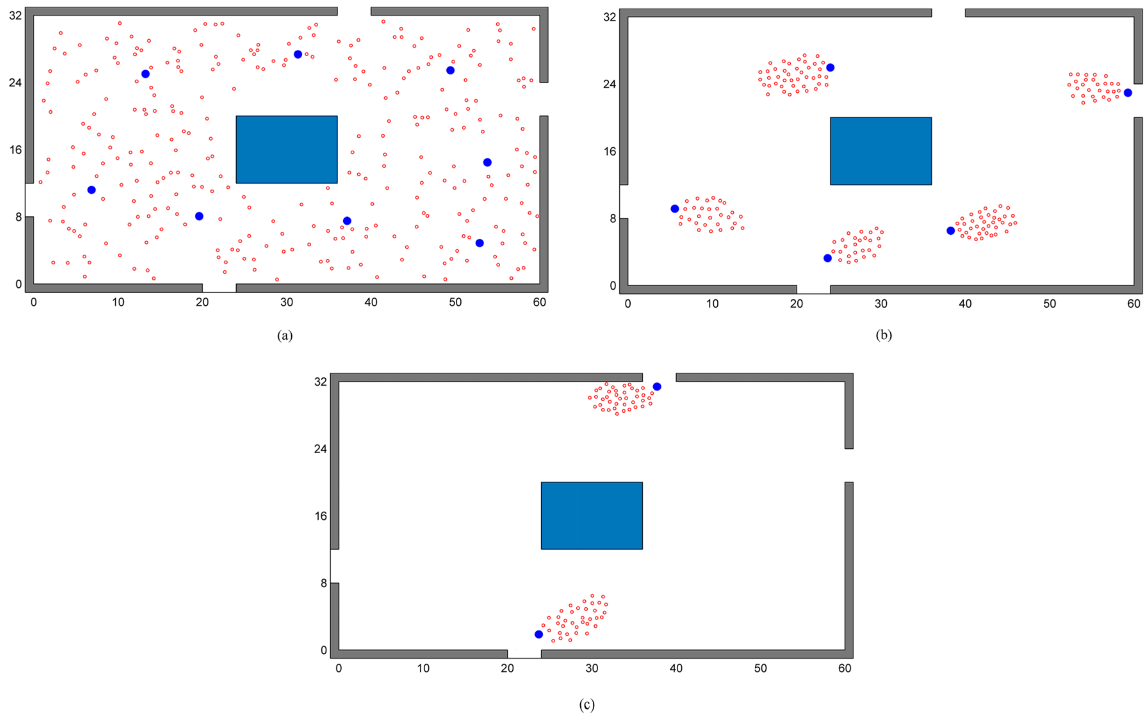


Fig. 8 The snapshots of the robot-guided crowd evacuation at a mall of the railway hub station

the hall. Based on the c-means clustering method proposed in Section 3, 8 robots are arranged in the hall as shown by the red dots in Fig. 8. The exit distribution and path planning schemes for robots are also generated taking into account evacuation distance and exit balancing. Passengers who near the exits began to evacuate from the direction of the exits. Other passengers search for the visual field then choose to follow a nearby robot for evacuation and move towards the exits. Then, some of the passengers distributed near the exit are evacuated out of the hall under the guidance of the robots. The remaining passengers are guided by the robots and formed 5 groups to move along the direction of the exits. From Fig. 8c we can see that almost all the passengers are evacuated in an orderly manner towards the exit under the guidance of the robots, and those farther away from the exit have arrived near the destinations. Eventually, the remaining passengers were successfully evacuated.

The utilization rate of the exits under the guidance of robots reflects the performance of the proposed schemes in terms of exit equilibrium. The number and proportion of passengers evacuated from each exit under different schemes were compared and analyzed from a quantitative perspective. The number (percentage) of evacuated passengers through four exits under the Opt_Dist scheme, Uni_Dist scheme, and No_Robot scheme are shown in Table 2. The number of evacuees at each exit under the three schemes shows a more significant difference. More passengers evacuate from the mall via Exits C and D than the other exits under the Opt_Dist scheme. The number of passengers evacuated from Exits A and C would be higher under the No_Robot scheme. In contrast, the number of evacuees at each exit is relatively balanced in the Uni_Dist scheme, because the initial distribution of passengers is randomly given.

Table 2 The number (percentage) of evacuated passengers through four exits under different robot distribution schemes

Scheme	The number (percentage) of evacuated passengers			
	Exit A	Exit B	Exit C	Exit D
Opt_Dist	65.18 (21.73%)	63.25 (20.08%)	94.16 (31.39%)	77.41 (25.80%)
Uni_Dist	80.32 (26.77%)	72.26 (24.09%)	86.48 (28.83%)	60.94 (20.31%)
No_Robot	85.24 (28.41%)	62.18 (20.73%)	88.32 (29.44%)	64.26 (21.42%)

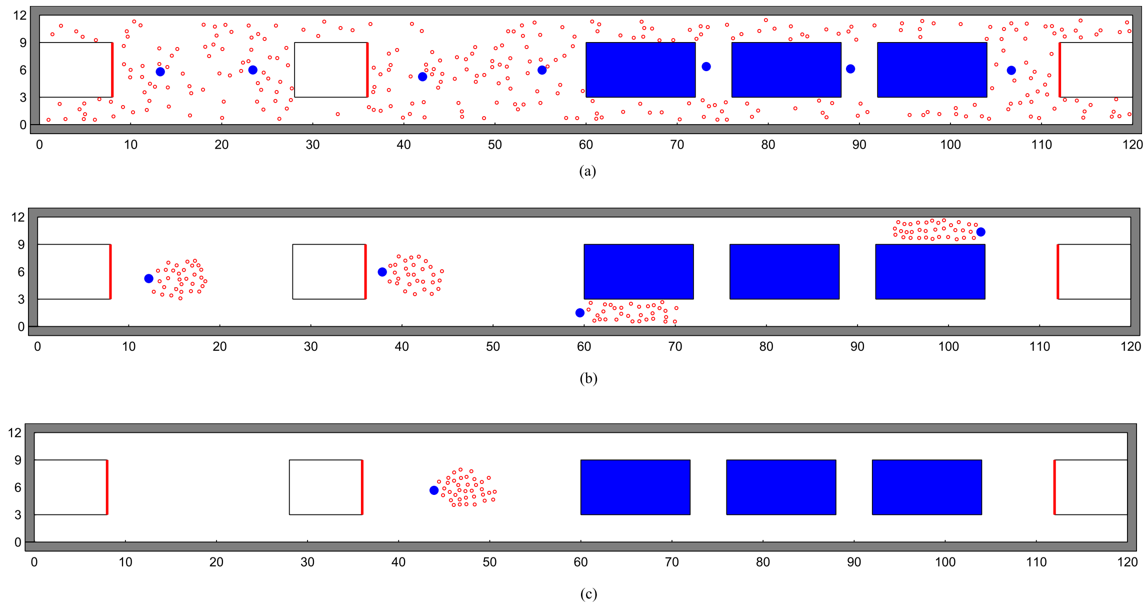


Fig. 9 The snapshots of the robot-guided crowd evacuation at a platform of the railway hub station

The scenario of the platform, as shown in Fig. 1b, is also chosen to further evaluate the effectiveness of the proposed method. It has an area of 1440 square meters with dimensions of 12 $m * 120$ m. Three entrances/exits are located on the left, middle, and right sides of the platform, which are recorded as A, B, and C from left to right. Three obstacles are located on the right side of the platform, each with a size of 12 $m * 6$ m.

The snapshots of the robot-guided crowd evacuation at a platform scenario are shown in Fig. 9. The initial positions and paths of robots are generated in the same way as that in the mall scenario. 7 robots are distributed in the platform based on the distribution of passengers. At the moment the evacuation begins, passengers who near the exits began to evacuate from the direction of the exits. Other passengers are searching for robots in their visual field and begin to follow them to evacuate. These passengers are divided into 7 groups and led by robots in the direction of the assigned exits. Most of passengers are successfully evacuated from the three exits, and some passengers reached near the exits by following the guidance of robots. But the number of passengers to be evacuated from each exit is uneven. Finally, only a group of passengers is left near Exit 2.

Table 3 Mean evacuation distance and mean evacuation time for different path planning strategies under the optimal distribution scheme

Strategy	Optimal Path	Shortest Distance
Mean Evacuation Distance (m)	20.62	18.56
Mean Evacuation Time (s)	56.24	64.52

We conduct the comparison of evacuation efficiency for different path planning strategies under the optimal distribution scheme. Table 3 gives a comparison of the mean evacuation distance and evacuation time under different path planning strategies under the optimal distribution scheme. Each individual is evacuated according to the shortest path, and the average evacuation distance is 18.56 m. This is a reduction of 2.06 m compared to the optimal solution. The frequency distribution of evacuation distance for different path planning strategies under the optimal distribution scheme is given in Fig. 10. The frequency of the evacuation distance under the optimal solution is lower

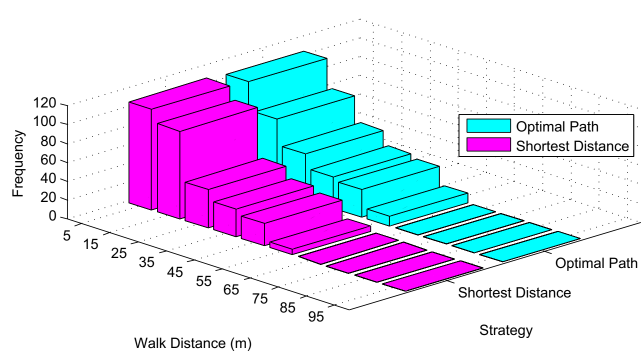


Fig. 10 Frequency of passenger walking distance for different path planning strategies under the optimal distribution scheme

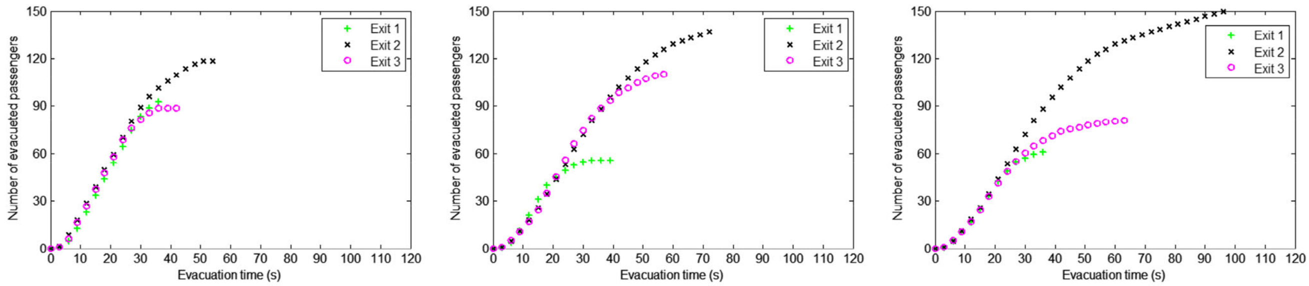


Fig. 11 Number of passengers on platform against evacuation time under three kinds of robot guidance schemes: (**a**) Opt_Dist scheme, (**b**) Uni_Dist scheme, and (**c**) No_Robot scheme

in the interval of 10 m-20 m than the shortest solution, and for evacuation distance, greater than 20 m is higher than that of the shortest solution. However, individuals all choose the shortest evacuation path, which does not guarantee the minimum evacuation time. The evacuation time is 12.8% lower than that under the shortest distance strategy. This is because the passenger evacuation process under the shortest distance strategy may lead to congestion in bottleneck areas such as corners and exits. For evacuation time, the individual optimum is not equal to the global optimum.

The number of passengers on the platform against evacuation time under different robot guidance schemes is shown in Fig. 11, which also reflects the utilization and balance of exits under different schemes. At the beginning of the evacuation, the evacuation speed of passengers at each exit is essentially the same under three schemes. The difference starts to appear after 30 seconds and gradually becomes larger, which is particularly evident in the No_Robot scheme with a lower utilization rate. After 60 seconds, a small number of passengers are still evacuated from Exits 2 and 3. In contrast, the proposed Opt_Dist scheme in this paper maintains a high utilization of each exit during the evacuation process. Compared with the No_Robot scheme, the Uni_Dist scheme improves the exit utilization and reduces the total evacuation time, but some passengers are still evacuated from Exit 2 after 60 seconds.

The number (percentage) of evacuated passengers through three exits under the Opt_Dist scheme, Uni_Dist scheme, and No_Robot scheme are shown in Table 4.

Table 4 The number (percentage) of evacuated passengers through three exits under different robot distribution schemes

Scheme	The number (percentage) of evacuated passengers		
	Exit 1	Exit 2	Exit 3
Opt_Dist	92.65 (30.88%)	118.57 (39.52%)	88.78 (29.59%)
Uni_Dist	55.25 (18.42%)	133.22 (44.40%)	111.53 (31.18%)
No_Robot	60.09 (20.03%)	159.03 (53.01%)	80.88 (26.96%)

Regardless of which scheme is used, Exit 2 evacuates the largest number of passengers, which accounts for more than 39% of the total. Conversely, Exit 1 evacuated the least number of passengers, which is less than 20% under the Uni_Dist scheme. The No_Robot scheme shows the most significant variability in the number of evacuees at each exit, in which Exit 2 occupies more than half of the total. The Opt_Dist scheme has the closest proportion of evacuees at each exit, showing good balance and the highest evacuation efficiency. The performance of the Uni_Dist scheme is in between the other two schemes.

The relationship between the number of passengers and evacuation time under different schemes is shown in Fig. 12. The evacuation time is defined as the time it takes for the last passenger to leave the platform. The number of evacuated passengers shows a non-linear relationship with evacuation time for the same scheme. The effect of the change in the number of passengers on the evacuation time is not significant in the No_Robot scheme. The number of passengers increased by 200, but the evacuation time increased by only 10 seconds. The evacuation time for 300 passengers under the Opt_Dist scheme is 56 seconds, which is a 14% and 10% increase over the time for 100 and 200 passengers, respectively. The evacuation time for the same number of passengers under the Uni_Dist scheme lies between the other two schemes.

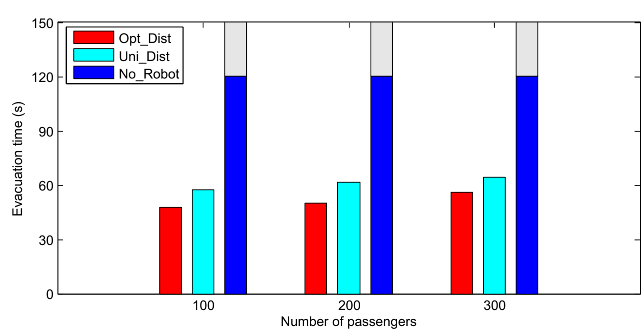


Fig. 12 The number of passengers against the evacuation time under different robot distribution schemes

5 Conclusion

The introduction of robots can provide passengers with effective evacuation information, such as safety exits and evacuation paths. In this paper, we proposed a multi-robot guided passenger evacuation method to help passengers search evacuation paths and avoid potential risks. Based on the initial distribution of passengers at the moment of the emergency event, the number and initial positions of robots were determined by using a k-means clustering approach. The optimal evacuation path was generated for each robot by using a hybrid bi-level optimization approach. Then, a modified social force model was proposed to describe robot-guided crowd evacuation dynamics, in which a navigation force was introduced to quantify the impact of robots on pedestrian movement. An inverse kinematic model was designed by direct controlling of the two-wheeled differential drive method.

The effectiveness of the proposed robot-guided evacuation scheme was demonstrated through a case study of a typical railway hub station. Two kinds of experiments at the scenarios of mall and platform were performed, respectively. The results show that setting up robots can effectively reduce evacuation time, and the utilization of exits is more balanced. The evacuation time under the optimal path planning strategy is 12.8% lower than that under the shortest distance strategy. The proposed optimal robot-guided crowd evacuation scheme showed the best performance with more than 30% lower evacuation time, compared to the uniform distribution scheme and no robot scheme. The number of passengers evacuated by each exit is more balanced under the Opt_Dist scheme. The proposed scheme can not only improve the evacuation efficiency but also has less congestion.

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