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A Model-based Analysis of Evacuation Strategies in Hospital Emergency Departments

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ABSTRACT

Evacuation planning for emergency incidents is an essential preparedness for Emergency Departments (ED) which normally contains patients with severe illness and limited mobility. However, the preparedness can be challenging due to a lack of empirical data and difficulties conducting physical drills. We propose an agent-based model to simulate the evacuation process in the EDs containing medical staff, rescuers, visitors and various types of patients. In a case study, we apply the model to a peak hour scenario of the ED of the largest hospital in Singapore. Two rescue strategies with different behavior sequences of medical staff as suggested by the practitioners are evaluated. The simulation results show that prioritizing preparation of all the patients generates less total evacuation time but leads to fewer evacuated cases in the first 20 minutes and more serious congestion compared to one-by-one transfer of individual patients.

1 INTRODUCTION

Evacuation planning for emergency incidents is an essential preparedness for healthcare systems. Healthcare facilities are required to have evacuation plans in response to the risks such as fire and chemical/gas spills (Taaffe et al. 2005; Golmohammadi and Shimshak 2011). Compared to other built environments

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such as shopping centers and schools, healthcare facilities contain large numbers of injured and sick people, making it difficult to conduct evacuation in a short time. Specifically, an Emergency Department (ED) consists of multiple functioning areas such as resuscitation rooms, critical care units, consultation rooms to serve patients with severe illness and limited mobility. As a consequence, the layout of an ED and the population of it can be more complex and therefore make the evacuation more challenging than other departments in the hospital.

Typically, evacuation plans are designed and supervised by incident managers from the healthcare facility (Jafari et al. 2008). The accessible exits and evacuation routes of pedestrians at different locations are designed in order to minimize the evacuation time and maintain the survival rates. However, these plans can only provide guidelines or best practices at very abstract levels. The behaviors of rescuers are not regulated from an industrial perspective. Besides, the plans cannot be easily updated or refined due to the following challenges: (1) data collection from real evacuations are limited as emergency incidents happen infrequently (Rahouti et al. 2020); (2) existing empirical data or documents from one healthcare facility may not be applicable to other facilities with different layouts; (3) revising the evacuation plans might require numerous physical evacuation drills, which can be time consuming and labor intensive (Taaffe et al. 2006).

One possible solution to address the above issues is to use simulation. In fact, numerical models have been widely used to reproduce the evacuation process of facilities and evaluate the performance (Mielczarek and Uziałko-Mydlikowska 2012). Among all, agent-based modelling becomes increasingly popular due to its ability to display the outcome on a macroscopic level and reveal the interaction on a microscopic level at the same time (Gutierrez-Milla et al. 2015). To this end, we present an agent-based model to reproduce the evacuation process for an emergency department setting and evaluate the performance of evacuation strategies. Our contribution can be summarized as follows:

- Behaviors of patients of different mobility, medical staff, visitors and additional rescuers from other departments are modeled based on existing literature and input from professionals at the ED of Singapore General Hospital (SGH).
- Two rescue strategies varying the rescue behavior sequences are presented and tested in the simulation.
- The performances of the two strategies are compared in terms of the time required for waiting for help and travelling to the place of safety as well as the distribution of overall evacuation time.

The remainder of this paper is organized as follows: Section 2 gives a literature review on related work. Section 3 presents the simulation layout and the underlying framework for decision making and collision avoidance. It also explains the characteristics of each character type. Section 4 describes the rescue strategies evaluated in the study. Section 5 presents the numerical simulations and discusses the results. Section 6 summarizes our work and provides possible research directions for the future.

2 RELATED WORK

Simulation models are widely used to support decision-making processes in the health care sector. For example, Taaffe et al. (2006) proposed a model to evaluate the effects of varying transportation and staffing plans. Haghpanah, F. and Foroughi, H. (2018) used genetic algorithms to optimize shelter location-allocation during evacuation. Those studies focus more on resource arrangement but pay little attention to the evacuation process in the hospital setting. In contrast, Yokouchi et al. (2017) simulated horizontal evacuation within a hospital ward using a discrete-event model. They estimated the total evacuation times for different evacuation priorities and various patient types based on a macroscopic pedestrian flow model. However, their model had limitations on reflecting the interaction between individuals during evacuation. Incorporating such behaviors is indispensable because interaction among individuals during evacuation affects the total evacuation time and might produce congestion or fatal delays (Wang et al. 2015; Chu et al.

2017). In Section3.3, we resolve the above issue by implementing the well-known Social Force Model with its extensions (Helbing and Molnár 1995; Curtis et al. 2013; Moussaïd et al. 2010).

Research regarding pedestrian behaviors during an emergency has been done in recent years, providing sufficient evidence for more plausible evacuee behavior modeling. Various literature has investigated the moving speed of disabled patients by conducting controlled experiments (e.g., walking with an assist from helpers (Boyce et al. 1999a) or with wheelchairs (Geoerg et al. 2019)). Kwak et al. (2021) analyzed the evacuation performance of horizontally moving patient trolley beds in corners and straight corridors in a healthcare facility. A decrease in moving speed due to the fatigue effect of the volunteers after several round trips were highlighted. In addition, some studies collected data on evacuee behaviors by analysing video recordings of fire drills (Purser and Bensilum 2001; Rahouti et al. 2020). Our model utilizes the results from existing works for parameter setup of the agent movement (discussed in Section3.3).

3 PEDESTRIAN MODEL

In this section, we describe a pedestrian model developed in the CrowdTools simulation framework (Cai et al. 2010; Su et al. 2019). An introduction of the layout of SGH ED is presented, followed by the description of characteristics and behaviors of each type of agent in the scenario, as well as the fundamental movement model of agents.

3.1 Scenario

We modeled the layout of SGH ED before the outbreak of COVID-19 into a color-coded map (see Figure 1). Patient slots (depicted by brown rectangles) indicate the possible placements of patients with wheelchair or trolley beds. 68 patients slots are located at the resuscitation room, critical care unit, observation rooms and isolation area based on our observation. 120 Seats (depicted by purple squares) for ambulant patients and their companies are placed at the waiting areas in the consultation area and triage areas. 21 rooms where medical staff provide one to one service or treatment to patients are located at the consultation area, triage area and isolation area. Thus, the ED is able to receive approximately 209 pedestrians (including patients and visitors) at one time. Three exits (Exit A, B and C) leading to the place of safety outside of the building are available for ambulant pedestrians during evacuation. Non-ambulant pedestrians (i.e., wheelchair users and trolley bed patients) should flee to the place of safety through Exits D1 or D2.

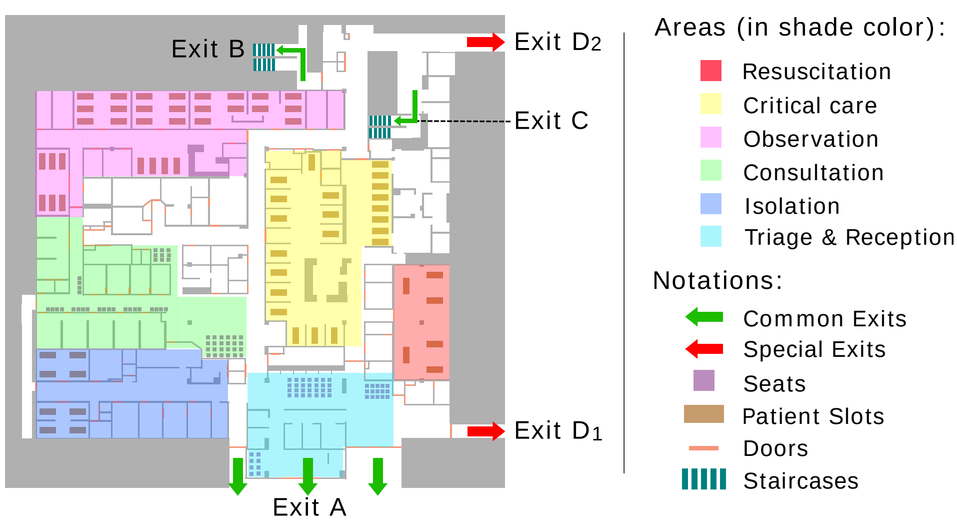


Figure 1: The floor plan of SGH ED Level 2.

Table 1: Characteristics of patient agents

Patient type	Representation	Helpers required	Preparation time	Distribution areas	Accessible exits	Triage class
Trolley bed	rectangular ($2m * 0.8m$)	2	5 to 7 mins	Resuscitation Critical care Observation Isolation	D1 and D2	P_1 or P_2
Wheelchair	rectangular ($0.6m * 0.6m$)	1	3 to 5 mins	Critical care Observation Isolation	D1 and D2	P_2
Ambulant	circular ($r = 0.25m$)	0 to 2	0	Isolation Consultation Waiting	A, B and C	P_3

3.2 Characters

We modeled four types of agents in this study: patients, medical staff, visitors, and rescuers. The behavior modeling of each agent type and assumptions were determined after consultation with the SGH ED facility manager and clinicians. Their definitions are as follows:

Patients: the individuals seeking treatment at the ED and incapable of moving as normal pedestrians. Depending on their ability to walk and their mobility, we categorized the patients into two types: non-ambulant patients (i.e., with either trolley beds or wheelchairs), and ambulant patients who are capable of walking. Non-ambulant patients are initialized at the patient slots. Two helpers are required to transfer a trolley bed patient and one to transfer a wheelchair patient. It is assumed that the non-ambulant patients are not able to flee without sufficient helpers (either medical staff or rescuers). Preparation process for the setup of portable life support devices and necessary treatments is required for non-ambulant patients before they can be transferred (Hunt et al. 2015; Strating 2013). The preparation takes 5 to 7 minutes for a trolley bed patient and 3 to 5 minutes for a wheelchair patient, following the uniform distribution similar to (Golmohammadi and Shimshak 2011). After the preparation is completed, the patient is sent to the place of safety through specific exits. In contrast, ambulant patients are assumed being treated in the corresponding rooms or waiting to be treated in the waiting areas. They are initialized randomly at the corresponding areas. The ambulant pedestrians do not need to use evacuation devices and life support devices, and thus do not require preparation. However, they still have to flee with a certain number of helpers depending on their condition (i.e., injury level). Patients are also categorized into three triage classes based on their severity for evacuation planning purposes, which will be discussed in Section 4. More details of the characteristics are presented in table 1.

Medical Staff: the nurses, support staff and doctors who provide care to patients in the ED. They are assigned to certain areas of the department based on the hospital roster provided by the department. For simplicity, medical staff are assumed to have prior knowledge of the locations of patients. During the evacuation, medical staff look for patients, perform preparation (if needed) and flee to the place of safety with patients. A certain number of staff are required to stay at the place of safety to provide medical support for the rescued patients (Taaffe et al. 2005). The remaining staff return to the ED to rescue the other patients in danger till all the patients are rescued.

Rescuers: the Civil Emergency Rescue Team (CERT) consisting of volunteers from other departments of SGH (SCDF 2021). The CERT members come to the place of danger through Exit D1 and D2 certain minutes after an emergency evacuation alarm has been activated. Their major priority is to transfer patients to the place of safety. Unlike the medical staff, rescuers are not allowed to render treatment or use any medical devices during the evacuation. Thus, rescuers do not perform evacuation preparation.

Visitors: the pedestrians accompanying or visiting patients. Before the evacuation starts, they are assumed to be sitting or standing in the waiting areas of the consultation or triage area. They flee to the nearest exits immediately when the incident alarm has been activated. Volunteering behaviors (Kwak et al. 2020) will be triggered if they happen to notice any ambulant patient along the way to the exits. However,due to safety concerns, visitors are not allowed to rescue non-ambulant patients. Re-entry to the ED is also forbidden for them.

3.3 Movement model

Our pedestrian movement model is implemented based on the framework in (Su et al. 2019), which consists of a high level module for decision making and low level module for distance-keeping and speed-adjusting.

The high level decision-making module is developed according to the Recognition-Primed Decision (RPD) paradigm (Klein 1997). The RPD helps an agent to select the best matching behavior by comparing the current circumstances to his previous experiences. The behavior can be adjustment of navigation destination or determination of action such as walking straight or standing still. The agent keeps executing the selected behavior until the goal of the behavior is achieved or a violating condition occurs. For example, a medical staff sets his navigation goal to his target patient. He/she will keep navigating until reaching the target (behavior achieved) or noticing that the target has been saved by other colleagues (condition violated). The navigation behavior is based on a hierarchical A* algorithm, which calculates the shortest path on both the navigation graph level and the grid level (Cai et al. 2010; Harabor and Botea 2008).

At the same time, the low level module provides force-based collision avoidance behaviors and speed control of agents. The collision avoidance mechanism is based on the well-known Social Force Model (SFM) (Helbing and Molnár 1995). The force affecting an agent i at time t is defined as follows:

$$m_i \frac{\mathrm{d}v_i}{\mathrm{d}t} = F_d + F_{obs} + F_{nb} + F_g \tag{1}$$

where m_i is the mass of the agent. F_d is the driving force affected by the difference between the actual velocity and desired velocity of the agent itself. F_{obs} is the repulsive force from the surrounding obstacles. F_{nb} in (1) is defined as $\sum_{j=1}^{n}(p_i - p_j)f_{ij}$, which is the sum of repulsive forces exerted by neighboring agents. p_i here is the priority level of agent i in the right of way extension of SFM (Curtis et al. 2013). This component adjusts the orientation of repulsive forces between agents. It is used for maintaining the dominant navigation priority of patients with moving devices against other pedestrians. Finally, F_g in (1) is the grouping forces exerted by the agents within a group (Moussaïd et al. 2010). It helps to keep the reasonable formation between a patients and his corresponding helper(s) during navigation to the exit.

Similarly to Kwak et al. (2020), the desired walking speed is assumed 1.2 m/s for a normal pedestrian who is not a patient. Desired speed for different injury levels of ambulant patients is defined as: 0.96 m/s (80% of walking speed of normal pedestrians) for injury level 0, 0.72 m/s (60%) for injury level 1, and 0.48 m/s (40%) for injury level 2, referring to Boyce et al. (1999b),. In line with previous studies by Geoerg et al. (2019), Kwak et al. (2021), the desired moving speed for a wheelchair patient or trolley bed patient is set as 1.07 m/s. According to Kwak et al. (2021), the movement speed of trolley bed and wheelchair patients decreases while turning and is also affected by the fatigue level of their helpers.

4 RESCUE STRATEGIES

The existing evacuation plan from SGH ED provides guidance on prioritizing patients to rescue. In general, patients who are nearer to the place of danger have higher priority to be rescued. In addition, all patients are categorized into three triage classes as defined in (NHS England 2021), i.e., P_1 (unconscious and in life threatened state), P_2 (conscious but cannot move without assisting devices) and P_3(can walk unaided at less than normal pace).

Medical staff and rescuers are assigned to one of the triage classes and take the responsibility for evacuating the corresponding patients, noted by S_c and R_c respectively, where $c \subseteq \{1,2,3\}$. However,

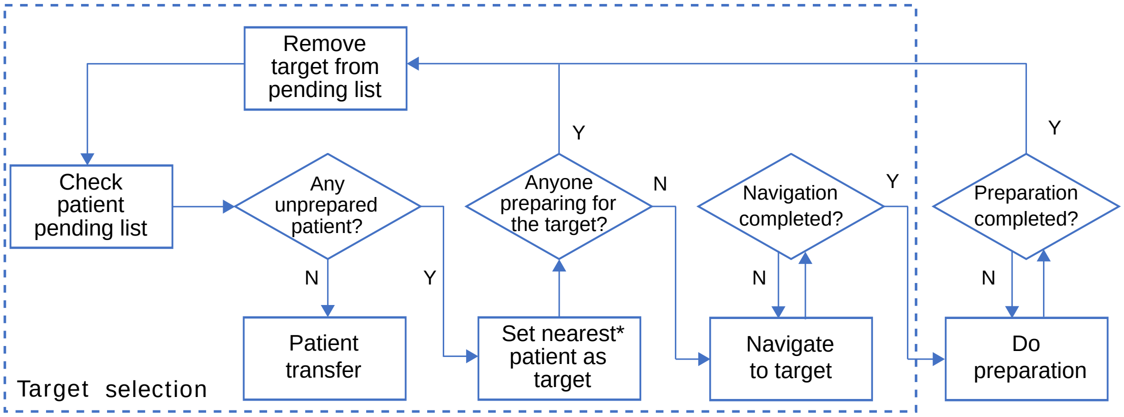


Figure 2: Decision-making process of Strategy 1 - Prioritizing preparation. *The nearest patient refers to the one that is the nearest to the place of danger.

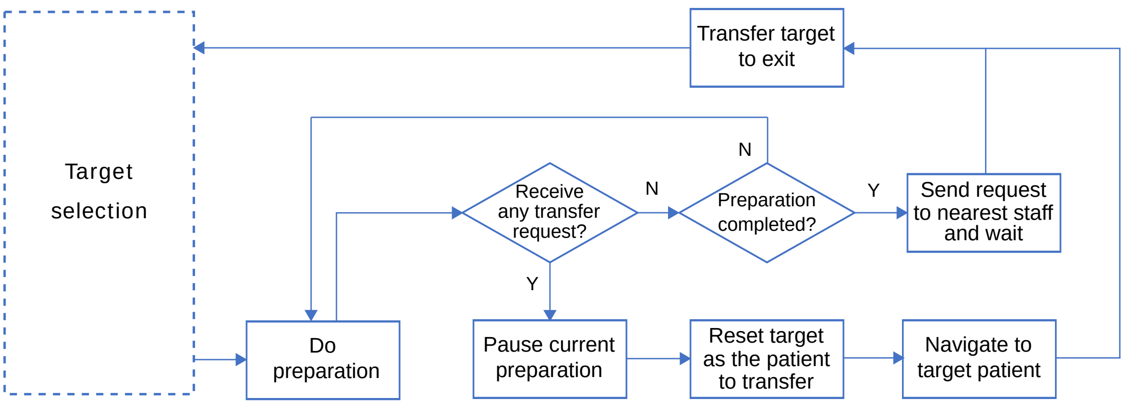


Figure 3: Decision-making process of Strategy 2 - Prioritizing transfer. The target selection process for is the same as Strategy 1.

medical staff are not allowed to perform cross-class rescue while rescuers are allowed to do so. For example, an S_1, who is responsible for triage class 1, can only evacuate P_1 as he/she is required to stay at the place of safety to provide subsequent care to P_1 after they have been rescued. On the contrary, an R_1 responsible for class 1 is allowed to save P_2 and P_3 patients after all P_1 have been completely evacuated.

In addition to the priority of triage classes, we provide two strategies restricting the behavior sequences for medical staff while rescuing patients. The Strategy 1 ”Prioritizing Preparation” is shown in figure 2. When the evacuation starts, each staff is assumed to have a pending list of patients in his/her responsible triage class. A staff queries the list and navigates to the unprepared patient that is the nearest to the place of danger and conducts preparation. He/she will change the target to another patient once the preparation is completed or the target has been taken care of by other staff. Patient transferring will be executed only after all the preparation for the assigned patients is completed. Strategy 2 ”Prioritizing Transfer” is shown in figure 3. It shares a similar target selection process with strategy 1. However, when a staff completes preparation for the current target, he/she immediately sends a transfer request to the nearest staff and waits for assistance. The staff receiving the request pauses his/her current task and assists the request sender to transfer the patient to the place of safety. Evacuation using both strategies is numerically tested and evaluated in Section 5.

5 CASE STUDY

In this section, we utilize the presented model to perform a series of numerical simulations to evaluate the performance of rescue strategies given in Section 4. We also have a discussion on the results as well as the limitation of the case study.

The following metrics were measured for each patient:

- Waiting time (t_w): the time from when the event begins to the moment when the patient is prepared and ready to be evacuated. Specially, $t_w = 0$ for ambulant patients of injury level 0.
- Travel time (t_t): the time from when the patient starts to evacuate to the moment when he/she reaches the specific exit.
- Evacuation time (t_e): the time required on the total evacuation process by a patient. The evacuation time is assumed as a sum of waiting time and travel time, i.e., $t_e = t_w + t_t$.

The average and maximum values of these metrics were calculated for patients of different triage classes (i.e., P_1, P_2 and P_3). The maximum t_e of a triage class also indicates the time when the last patient of the class arrived at the specified exit, and the maximum t_e among all three classes reveals the time consumed for the whole evacuation process. 20 runs were conducted on the CrowdTools (Cai et al. 2010) for each rescue strategy with random initial positions of agents and required preparation times of non-ambulant patients. The 95% confidence intervals of the above values were computed to examine the stability of the model.

In the case study, we focus on an extreme case where the evacuation happens during peak hours, when all patient slots, seats and consultation rooms in the department are fully-occupied. The fire is assumed to start at the south of the ED, blocking access to Exit A. Thus, all the occupants have to evacuate to the place of safety through Exit B, C and D2 located at the north. In such a scenario, 165 patients including 6 P_1 and 31 P_2 on trolley beds, 31 P_2 on wheelchairs, and 97 P_3, 59 medical staff ($S_1 = 4$, $S_2 = 30$, $S_3 = 25$) and 60 visitors are initialized before the evacuation starts, while 42 rescuers ($R_1 = 12$, $R_2 = 15$ and $R_3 = 15$) will arrive from neighboring buildings through Exit D2 in around 15 minutes. The initial conditions above are based on the staff roster documents and recommendations from facility managers and emergency physicians.

The results are shown in Figures 4 and 5. Both strategies provide similar average evacuation times for all patient types. However, Strategy 1 outperforms Strategy 2 in terms of the maximum evacuation times, taking 28.6% less time (19.2 mins) than Strategy 2 (26.9 mins) for P_1 patients, and 26.0% and 10.0% for P_2 and P_3, respectively. Similar results can be found for the waiting phase, where Strategy 1 takes 30.5% less time (17.3 mins) for $P1$ than Strategy 2 (24.9 mins), 28.2% and 22.0% for P_2 and P_3 respectively. One reason is that, with Strategy 2, extra travel between patients and the place of safety is made by medical staff before the arrival of rescuers, occupying the time for preparation. The extra travel also leads to fatigue effect, which reduces the transfer speed of medical staff during the later phase of rescue. Another possible reason is that, for Strategy 2, certain number of medical staff are required to stay at the place of safety for evacuated patients. That is, as the number of evacuated patients increases, fewer staff would go back to the ED for preparation. On the contrary, Strategy 1 avoids the above issues since the transfer of non-ambulant patients is only carried out after the preparation for all patients is completed.

However, the results also show the limitations of Strategy 1. Figure 4 shows the distribution of evacuation using different strategies. Although Strategy 2 eventually takes more time for the rescue, some patients are saved in a relatively short time. The distribution for all patients implies that, when given a time limit of less than 20 minutes (indicated by the red dot), more patients can be rescued with Strategy 2. The rescue for P_1 and P_2 using Strategy 1 starts later compared to Strategy 2. Especially, there is a sharp increase of the percentage of P1 and P2 patients rescued at around 15 minutes, at which the rescuers arrive. On the contrary, Strategy 2 provides a more gentle increase on both rescued P_1 and P_2, starting

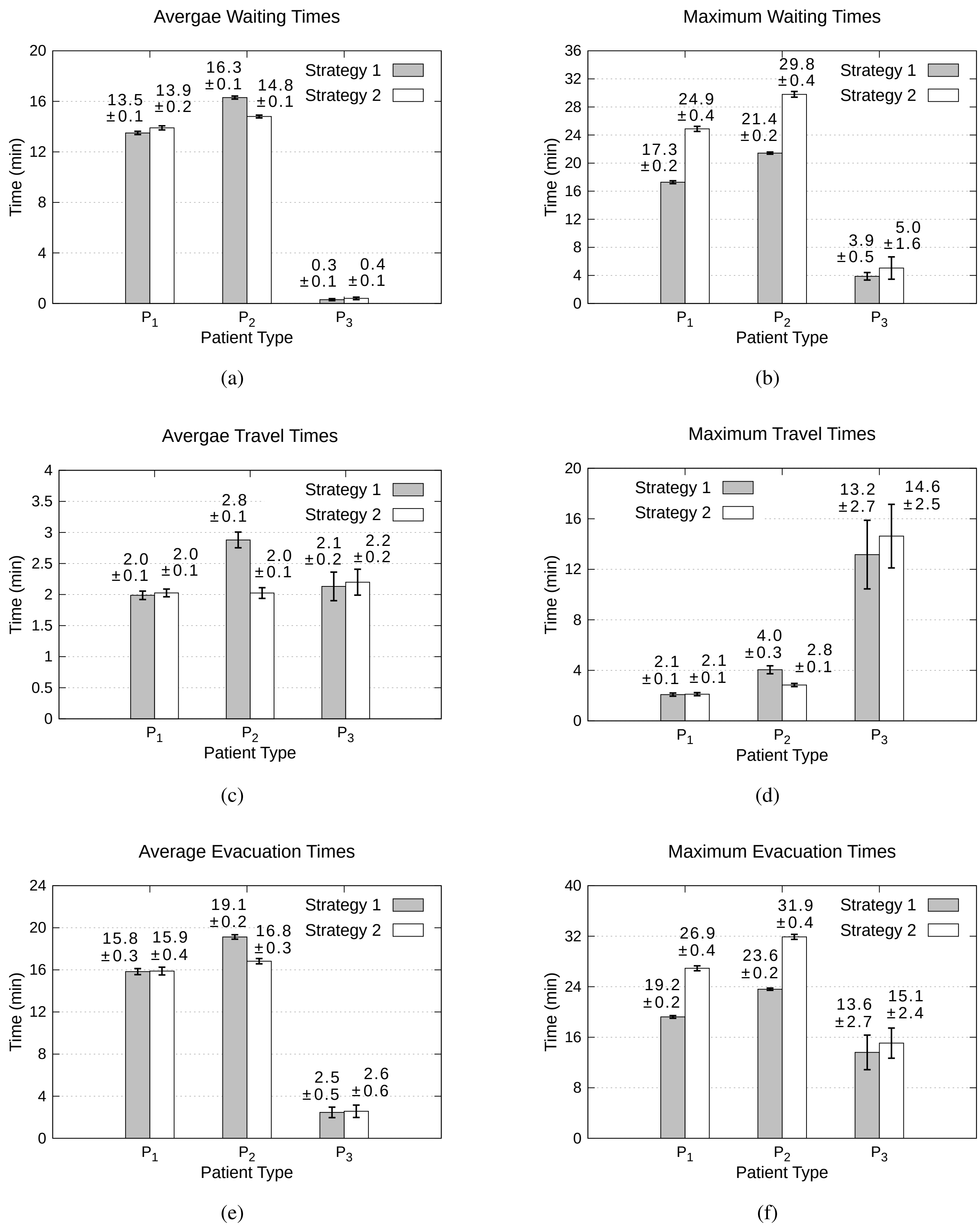
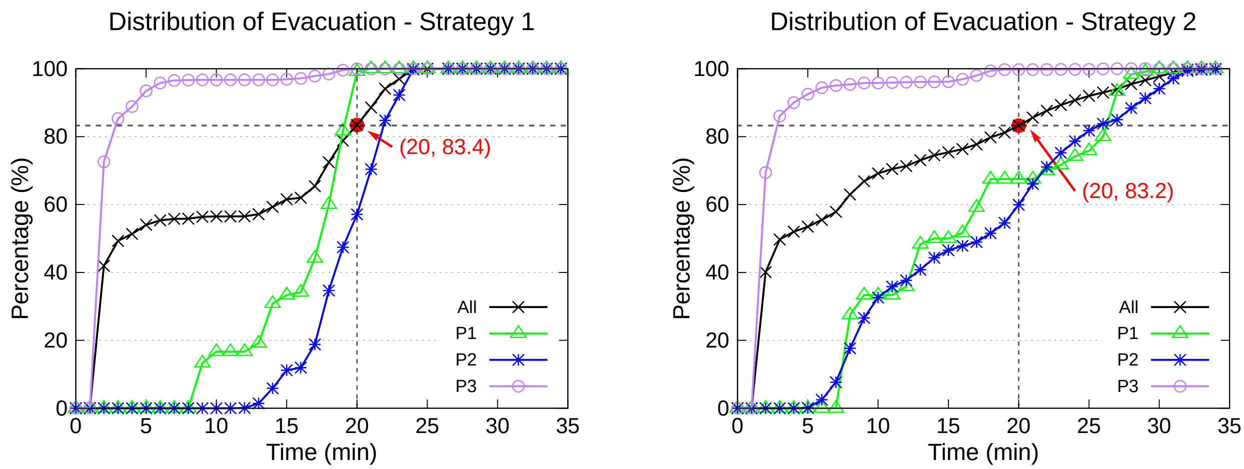


Figure 4: The average and maximum times of waiting, travel and evacuation process over 20 runs using Strategy 1 and Strategy 2. The error bars indicate the margins of error with 95% confidence intervals.



(a) (b)

Figure 5: Distribution of patient evacuation with (a) Strategy 1 and (b) Strategy 2. The red dot indicates the critical point when Strategy 1 starts to outperform Strategy 2 considering the evacuation of all patients.

from 5 minutes. There is no noticeable difference on the evacuation of P_3 patients. It is because most of P_3 patients are able to walk independently.

The sharp slopes of P_1 and P_2 curves in Figure 5a reveal another limitation of Strategy 1, that is, a large number of wheelchair and trolley bed patients starts to evacuate within a short period of time, leading to potential congestion on the way to the exit. As shown in Figure 6, one can see severe congestion in bottlenecks, such as exits of observation rooms and critical care units, and corner sections. Consequently, the average travel time of Strategy 1 (2.9 mins) is 45.0% greater than that using Strategy 2 (see Figure 4c).

Although the comparison is based on specific patient distribution and the fire location, the result is still useful for providing practical recommendations. For example, in an extremely severe incident where the key objective is to evacuate as many patients as possible before the arrival of rescuers, Strategy 2 can be a better choice. It is also a better choice to reduce congestion in a less severe incident where evacuation is allowed to be completed in a longer time (30 mins in our case study). On the other hand, Strategy 1 is preferred if the acceptable evacuation time is between 20 to 30 mins and the total evacuation time is the key concern to be minimized. Note that the intention of the case study is to show the ability of the model to demonstrate the evacuation process under particular situations and to provide numerical results. The case study considered only peak hour situation. When patient loading in the ED is different, the two strategies may generate different results. The model can be also utilized for other analysis such as the optimization of number of rescuers required and selection of evacuation routes.

6 CONCLUSION AND FUTURE WORK

We present an agent-based pedestrian model for simulating ED evacuation. The presented model considers the behaviors of medical staff, visitors, rescuers and different types of patients. The rescue policies of medical staff and rescuers are defined based on the existing guidelines from the Emergency Department. As a case study, the model was applied to the numerical simulations of two rescue strategies: prioritizing preparation for patients and prioritizing transfer of patients. Prioritizing preparation generates a shorter total evacuation time. However, congestion might occur in the process of evacuation. On the other hand, prioritizing the transfer generates a longer total evacuation time. But, a certain number of patients can be rescued earlier seemingly due to the early initiation of transfer.

One limitation of the presented model is the lack of validation. Although the individual agent behaviors have been validated based on existing literature, there are very few materials for us to evaluate the correctness

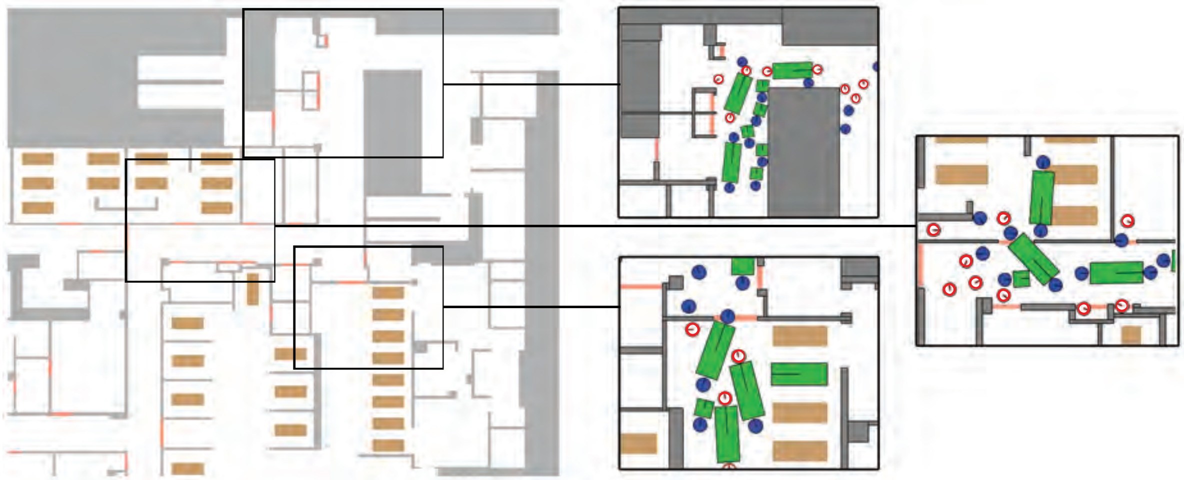


Figure 6: The congested regions commonly occurring during evacuation with Strategy 1. The zoom-in views are screenshots of a simulation run at different moments: the red hollow circles represent the medical staff; the blue circles represent the rescuers and green polygons represent patients with trolley beds or wheelchairs.

of the simulation results. To address the issue, mock-up experiments or real-world observations at the hospital may be considered for data collection in the future. Meanwhile, we are planning to define and evaluate more rescue behavior sequences of medical staff. Combinations of the strategies will also be considered, where medical staff selects one particular strategy based on the locations of target patients. We will also explore evacuation planning and parameterize the decision policies from other perspectives. For instance, we are currently conducting numerical experiments to find out the optimal number of required rescuers in scenarios with various patient distributions. We will also identify congestion in terms of crowd density to improve the evacuation routes and timings of patients.

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