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SIMULATION-BASED ANALYSIS OF EVACUATION ELEVATOR ALLOCATION FOR A MULTI-LEVEL HOSPITAL EMERGENCY DEPARTMENT

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ABSTRACT

Evacuation planning for hospital emergency departments is challenging because of the large number of patients with limited mobility due to severe illness. For trolley-ridden patients, elevators are often the only available mode for vertical evacuations. Thus, allocation of trolley-ridden patients to elevators is important to reduce vertical evacuation time with limited number of elevators. We developed a simulation model of vertical evacuation using elevators and applied the model to the future Singapore General Hospital emergency department as a case study. In the case study, we divided trolley-ridden patients into several groups based on their locations and evaluated the maximum evacuation time for various allocation setups. Simulation results show that evacuation on the lower level is sensitive to the allocation on the upper level. The overlapping utilization of the shared elevator by each level may lead to long queuing time at the lower levels and consequently increase the overall evacuation time.

1 INTRODUCTION

Evacuation planning for emergency incidents such as fire and chemical/gas spills is an essential preparedness for healthcare systems (Taaffe et al. 2005; Golmohammadi and Shimshak 2011). Compared to other built environments such as shopping centers and schools, healthcare facilities contain large numbers of injured and sick patients which increase the difficulty of evacuation. In particular, for an Emergency Department (ED), which consists of multiple functioning areas such as resuscitation rooms and critical care units to serve patients with severe illness and limited mobility, the evacuation can be extremely challenging.

Generally, pre-design of evacuation plans by incident managers from the healthcare facility is required while the building is still under construction (Jafari et al. 2008). The evacuation routes of pedestrians and allocation of resources are designed to minimize the evacuation time and maximize survival rates. However, these plans can only provide guidelines or best practices at very abstract levels. They cannot be analyzed or validated from an industrial perspective by any physical means until the construction is completed.

A possible solution to the above issues is to use simulation. Numerical models have been widely used to reproduce evacuation processes and evaluate the performance (Mielczarek and Uziałko-Mydlikowska 2012). Agent-based modeling is increasingly popular due to its ability to display the simulation outcome on both macroscopic level and microscopic level (Gutierrez-Milla et al. 2015). In our previous study, we proposed an agent-based evacuation model for the analysis of evacuation strategies conducted by medical staff in ED (Su et al. 2021). In this paper, we extend the model to incorporate the vertical evacuation. Our contribution can be summarized as follows:

- We further extended the pedestrian model of trolley-ridden patients, medical staff and rescuers based on existing literature and input from professionals at the ED of Singapore General Hospital (SGH).
- We developed an elevator model for low-rise buildings and the corresponding queuing, boarding and alighting model specially for trolley-ridden patients.
- We performed a case study for optimizing the allocation of patient groups to evacuation elevators with the presented model

The remainder of this paper is organized as follows: Section 2 gives a literature review on related work. Section 3 presents the pedestrian model and the elevator model. Section 4 presents the numerical experiments and discusses the results. Section 5 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, Haghpanah and Foroughi (2018) proposed a model to optimize shelter location-allocation during evacuation using the genetic algorithm. The study focuses on resource allocation while paying little attention to the evacuation of individual pedestrians. On the contrary, Yokouchi et al. (2017) simulated horizontal evacuation in a hospital ward using a discrete-event model and estimated the evacuation times for different evacuation priorities and various patient types. However, the discrete-event model had limitations on reflecting the interaction between individuals during evacuation. Incorporating such behaviors is indispensable because interaction among individuals during evacuation can have an impact on the total evacuation time and cause congestion or fatal delays (Wang et al. 2015). Our previous study resolved the issue by using agent-based modeling to evaluate the performance of rescue strategies executed by medical staff (Su et al. 2021). However, the model was only suitable for single-level scenarios and vertical evacuation was not considered. We extend the model in this paper by introducing the elevator model and the corresponding pedestrian behaviors to simulate multi-level evacuation.

In fact, evacuation in modern health facilities often involves multiple levels where vertical evacuation is needed. Chen et al. (2020) simulated evacuation in a high-rise nursing home, where the elderly were evacuated using both elevators and staircases. Andrée et al. (2016) studied exit choice and waiting times for evacuation elevators in high-rise buildings with the help of Virtual Reality (VR). Butler et al. (2017) had interviews with participants with mobility impairments (aided by wheelchairs, crutches and etc.) to identify perspectives on the use of elevators during fire evacuations. However, the mentioned research usually assumes ambulant evacuees or at least not bulky moving assist devices. In this paper, we focus on the patients with severe illness that cannot be transported without trolley beds. To evacuate these patients, the only available mode of vertical movement is to use evacuation elevators. The mobility of trolley beds is restricted by their size and weight, making the evacuation process much more difficult compared to that for ambulant pedestrians.

Research on the behaviors of patients with different levels of mobility has been done in recent years, providing sufficient evidence for more plausible evacuee behavior modeling. For example, Geoerg et al. (2019) conducted controlled experiments on the movement of wheelchair patients and its impact on the evacuation bottlenecks. Boyce et al. (1999) studied the egress capabilities of disabled people. Kwak et al. (2021) analyzed the performance of horizontally moving patient trolley beds in corners and straight corridors in a healthcare facility. Deceleration at corner sections was found and a gradual decrease in moving speed after several round trips due to fatigue effect were highlighted in that paper. The presented results were implemented in our model to achieve plausible movement of trolley-ridden patients.

3 MODEL

In this section, we introduce an evacuation model which is an extension of the work presented in Su et al. (2021). The underlying modeling of pedestrians of different characteristics will be introduced, followed by an elevator model and the pedestrian interaction with elevators including queuing, boarding and alighting.

3.1 Pedestrian Model

The agent-based pedestrian model was developed in a CrowdTools simulation framework (Cai et al. 2010; Su et al. 2019), which consists of the modeling of two levels of behaviors. The high-level decision-making model is based on the Recognition-Primed Decision (RPD) paradigm (Klein 1997). It determines the proper actions to execute by an agent under different circumstances (e.g., moving or idling) as well as the navigation goals. The low-level movement model is for collision avoidance. The collision avoidance was based on the well-known Social Force Model (SFM) (Helbing and Molnár 1995). The SFM was extended with the Right Of Way (Curtis et al. 2013), allowing agents to perform give-way behaviors to avoid head-on collision, and the grouping force (Moussaïd et al. 2010), which preserves the formation for agent groups while navigating (e.g., non-ambulant patients with helpers).

We defined the evacuation behaviors of different agent types as below:

Patients refers to individuals seeking treatment at the ED and incapable of moving as normal pedestrians. In this paper, we assumed that all the patients were of Triage Class 2, defined in the standard of NHS England (2021), i.e., not under life-threatened state but cannot move independently. When an incident occurs, these patients stay in the trolley beds and wait for the rescue. Two helpers (either medical staff or rescuers) are required for transferring a trolley-ridden patient. A preparation process (the setup of portable life support devices and necessary treatments) is needed before a patient can be led to the place of safety (Hunt et al. 2015; Strating 2013). The preparation process takes 5 to 7 minutes following the uniform distribution (Golmohammadi and Shimshak 2011).

Medical Staff refers to the nurses, support staff and doctors who provide care to patients in the ED. During the evacuation, medical staff are responsible for performing preparation for patients and transferring them to the place of safety. The medical staff always prioritize the patients closer to the place of danger, according to existing evacuation plans provided by SGH ED (Su et al. 2021). We also assumed that medical staff use the rescue strategy "Prioritizing Preparation" (Su et al. 2021), where they perform preparation for all patients on the same level before they proceed with transfer.

Rescuers refers to the Civil Emergency Rescue Team (CERT) formed by volunteers from other departments of SGH (SCDF 2021). Unlike the medical staff, rescuers are not assumed to have medical knowledge and thus are not able to render treatment or use any medical devices during the evacuation. Their only responsibility is transferring patients to the place of safety.

3.2 Evacuation with Elevator

Evacuees, especially non-ambulant patients, travel to lower levels using evacuation elevators. In this section we introduce the elevator model and the corresponding interacting behavior of pedestrians.

3.2.1 Elevator Model

An elevator entity is composed of three modules: Operator, Cabin, and multiple Lobbies (Sorsa et al. 2018):

Operators are responsible for scheduling the travel of elevators according to the requests sent from queuing passengers at lobbies and the requests sent by the passengers aboard. These requests are stored in the request list L, and sorted by a scheduling algorithm whenever a new request is received. The first request of L after sorting will be updated to the cabin as the target level l. The implemented scheduling algorithm is based on the SCAN Algorithm (Wei et al. 2020), where the elevator continues to travel in its current direction (up or down) until empty, stopping only to let individuals off or to pick up new individuals heading in the same direction. The operator monitors the occupancy of the cabin and no longer responds to the requests from lobbies when the elevator is full.

Cabins handle the traveling behaviors of the elevator. Figure 1 shows the workflow of a cabin designed in the Finite State Machine (FSM) framework (Gladyshev and Patel 2004). A cabin can either start at Stage-Free or Stage-Invalid depending on the scenario setup. At Stage-Free, the cabin keeps querying the operator until a target level l is decided. At Stage-Moving, it travels to l at a certain speed while keeping aware of the update of L by the operator. When it reaches l, it changes to Stage-Waiting until the boarding or alighting actions of passengers are completed. It then checks the emptiness of L and decides the next stage (Stage-Moving or Stage-Free) accordingly. The travel duration between two levels is estimated at 10 seconds, which is a common value for elevators in low-rise buildings (Elevator Community Wiki 2022). The duration of elevator gate opening and closing is estimated at 4 seconds after the last alight (Department for Communities and Local Government 2009). The cabin also stores the passengers on board in a passenger list P which is updated by the lobbies.

Lobbies are responsible for controlling the elevator gates and handling the passenger boarding and alighting process. To manage the boarding process, the lobby monitors the intended travel directions (upward or downward) of the queuing passengers. When the elevator arrives, the lobby first checks the passenger list P and re-inserts the passengers (if any) into the scenario according to their target levels. It then calls for the queuing passengers with the same intended travel direction as the elevator until the cabin is full (will be further discussed in section 3.2.2). The passengers successfully boarded are added to P and temporally removed from the scenario.

It is worth pointing out that the presented elevator model leads to a remarkable circumstance where the place of safety is at the ground floor and evacuees on upper levels are going to travel downward. When receiving the calling requests from the evacuees on multiple levels, the operator always suggests the highest level as the first destination for picking up evacuees, followed by the second highest level and so on. In this case, the evacuees at lower levels have a relatively lower chance to get on board due to the limited elevator capacity. As a result, the evacuees at higher levels always have the dominant priority to occupy elevators, namely the High Level First(HLF) rule.

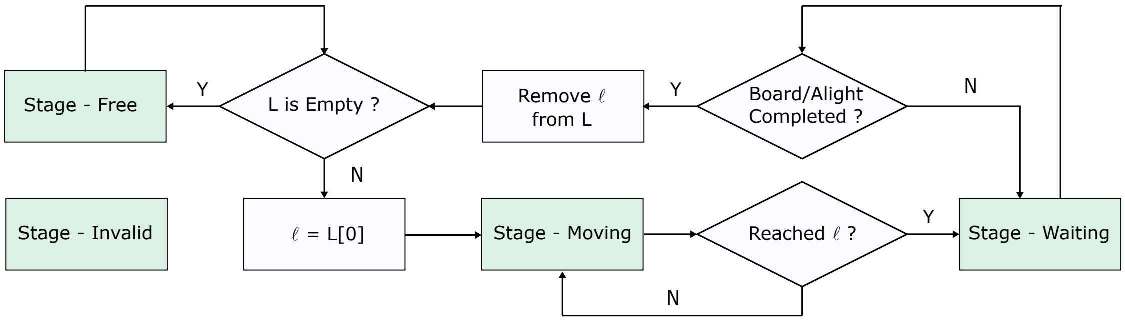


Figure 1: The workflow of an elevator cabin.

3.2.2 Queuing Behavior of Patients

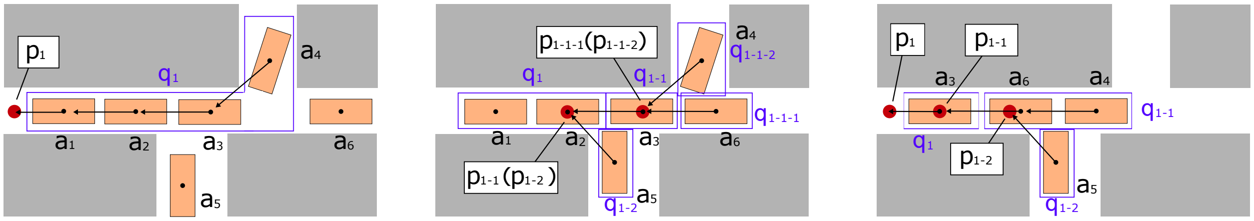
Compared to ambulant pedestrians, trolley-ridden patients have more difficulty performing re-orientation, turning and lateral movements due to the large volume and limited flexibility of moving devices. The force-based collision avoidance model may fail to solve the conflict due to the confined space for adjustment (Su et al. 2020). In this section, we introduce a method to generate the queuing behavior of trolley-ridden patients by adjusting their navigation goals to avoid the gathering of trolley-ridden patients at elevator lobbies.

We define a queue segment as $q = \{A, p, q_p, Q_c\}$, where A is the list of agents in the segment, p is the waiting point, q_p is the parent segment, and Q_c is the list of child segments. Specially, the root queue segment has an empty q_p and its p is located at the lobby center. The navigation goal of the first queuing member is set to p, while the others are pointing to their former member (see the agents in q_1 in Figure 2a). When an agent decides to evacuate through an elevator, it heads to the p of the root queue segment. There are two cases while joining the queue. The first is where the agent successfully reaches the last member of either queue segment (see a_4 joins at the end of the q_1 in Figure 2a). The agent is added the to agent list A of the segment and his/her navigation goal is then updated from the root p to the followed queuing member a_3. The other case is where the agent reaches a member in the middle of a queue segment instead of the end (see Figure 2b). When a_5 is approaching the queue in between a_2 and a_3, the original segment q_1 is decomposed into three parts: one with the former members (a_1 and a_2), a new child segment with the latter members (a_3 and a_4) labeled as q_{1-1}, and the other child segment with a_5 labeled q_{1-2}. The child segments are added to Q_c of q_1 and their waiting points are set to the current position of the last member of their parent (p_{1-1} and p_{1-2}). Similarly, when a_6 is approaching in between a_3 and a_4, the segment q_{1-1} is further decomposed into three parts, i.e., q_{1-1}, q_{1-1-1} and q_{1-1-2}. Note that the two child segments are labeled depending on the obstruction of their leading members. Here, the segment with a_6 is labeled as q_{1-1-1} because it is collision-free from the other child q_{1-1-2}.

When the elevator arrives, the lobby checks the intended travel direction of the members in the root queue segment. Those meeting the requirement are removed from the queue and board (restricted by the elevator capacity). The remaining members update their navigation goals and keep maintaining a configurable distance to their goals. Figure 2c shows the merge of segments when the parent segment q_1 is cleared. Every first child segment at each branch becomes the new parent segment of its branch (q_{1-1} becomes the new q_1 and q_{1-1-1} becomes the new q_{1-1}). The other child segment of the branch keeps waiting until the last member of the new parent passes its goal. For example, q_{1-1-2} with the agent a_4 merges into the new q_{1-1} when its last member a_6 has passed p_{1-1-2}.

4 CASE STUDY

In this section, we present two case studies using the layouts of the Emergency Department (ED) of the future Singapore General Hospital (SGH). We first conduct a numerical experiment with the presented



(a) (b) (c)

Figure 2: Queuing behavior of trolley-ridden patients: (a) patient a_5 and a_6 joining the queue segment, (b) q_1 is decomposed into sub-segments and its child segment q_{1-1} is further decomposed, and (c) the segments are updated and merged as the parent segment is cleared.

evacuation model to explore the optimal evacuation elevator allocation for trolley-ridden patients. With the findings, we then conducted an experiment to optimize the rescue team size for each level. A discussion on the results as well as the limitation of the case studies is presented at the end.

4.1 Scenario

Figure 3 shows the sketch of the floor plans of the future SGH ED Level 4 and Level 5. The brown rectangles indicate patient slots which are the possible placements of trolley-ridden patients, located at the critical care units, observation areas and wards. The red squares indicate the possible placements of medical staff located at nurse stations and offices. The yellow blocks indicate the evacuation elevators, two located at the central area and one located at the top right corner. The elevators in the department can only load one trolley bed per travel due to the limited capacity.

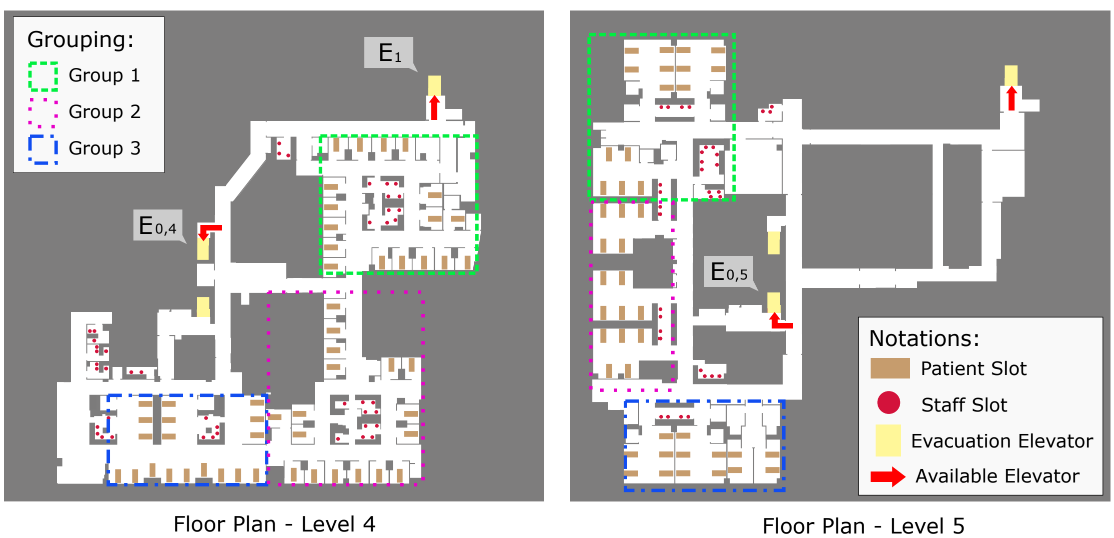


Figure 3: The sketch of the floor plans of the future SGH ED Level 4 and Level 5 (areas not involved in the experiment are hidden). Elevator $E_{0,4}$ and $E_{0,5}$ are strictly accessible to Level 4 and Level 5 respectively, while E_1 can be accessed by both levels.

The following case studies were conducted with the at-capacity scenario, where patient slots are fully occupied (52 trolley-ridden patients on Level 4 and 44 on Level 5) and the medical staff are assigned based on the roster for busy hours provided by the ED (20 on Level 4 and 9 on Level 5). The fire is assumed located at the south of the building, and patients closer to the place of danger should be evacuated with

Table 1: Patient Group information.

Patient Group	$G_{1,4}$	$G_{2,4}$	$G_{3,4}$	$G_{1,5}$	$G_{2,5}$	$G_{3,5}$
Number of Patients	17	17	18	15	15	14
Distance to $E_{0,l}$ (m)	56.9	72.9	56.7	74.1	59.4	41.0
Distance to E_1 (m)	39.3	80.2	96.8	77.9	101.3	114.6

higher priority. Rescue teams are assumed to arrive at the relevant levels before the evacuation starts. 10 rescuers are inserted at random locations on each level when the simulation begins for simplicity. Patients should be evacuated to the safety level (Level 3) through the evacuation elevators. Prior experiments showed that the pedestrians at Level 3 should have been cleared before any trolley bed patients from upper levels arrive. Considering the low arrival rate of the trolley bed patients through elevators, it is safe to assume that there will not be any potential congestion at Level 3 during the evacuation of Level 4 and Level 5. Therefore, we did not consider the navigation on the safety level in the case study.

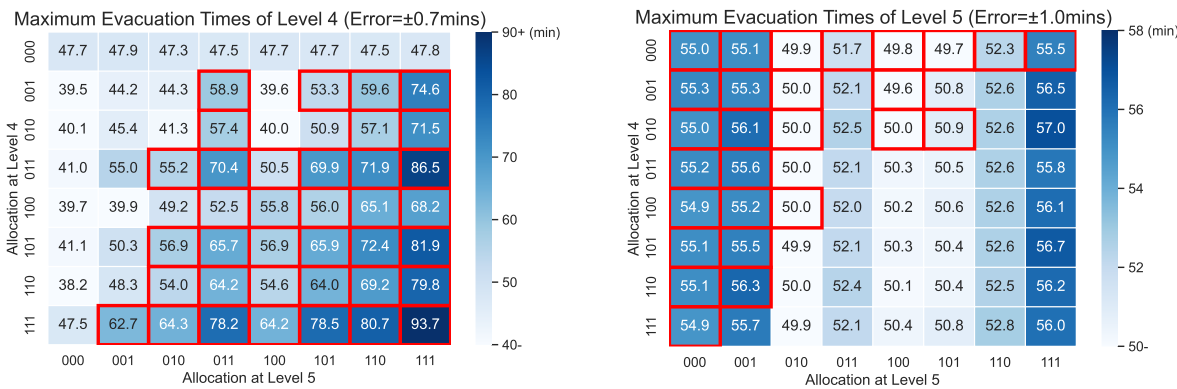
4.2 Evacuation Elevator Allocation Experiment

In this case study, we used the region-based method (Kurdi et al. 2018; Abdelghany et al. 2014) to optimize the allocation of evacuation elevators for the trolley-ridden patients on Level 4 and Level 5. Each level l has access to one of the exclusive evacuation elevators (noted as $E_{0,l}$) located at the center, and the shared elevator (noted as E_1) located at the top-right corner (see the red arrows in Figure 3).

The patients were divided into three groups at each level (noted as $G_{i,l}$, where $i = \{1,2,3\}$ is the group index and $l = \{4,5\}$ is the level). The travel distance from a group to an evacuation elevator was calculated using the location of the group (the average coordinates of the patient slots within the group) to the location of the elevator. The group size and distance are presented in Table 1. Each patient group was allocated to either $E_{0,l}$ or E_1, noted by $A(G_{i,l}) = \{0,1\}$ accordingly. An allocation at Level l is denoted by A_l. For example, $A_4 = 001$ is the allocation on Level 4 where $G_{1,4}$ and $G_{2,4}$ are allocated to $E_{0,4}$ and $G_{3,4}$ is allocated to E_1. There are 8 different allocations for each level and therefore 64 combinations in total for the scenario. The combination of allocations on Level 4 and Level 5 is denoted by $A = [A_4, A_5]$.

The evacuation time of a patient is measured using the time from when the event begins to the moment when the patient reaches the safety level. The maximum evacuation time of Level l, which is the time when the last patient on the level has been rescued, indicates the time when the evacuation on the level is completed. We also measured the number of arrivals $A(t)$ and the number of departures $D(t)$ to compute the queue length $Q(t) = A(t) - D(t)$ at a time step t (Daganzo 1997) for each elevator lobby. Each elevator allocation was simulated 20 times with different random seeds, and therefore 1280 runs in total were conducted for the experiment. The margin of error with 95% confidence intervals of each was 0.7 minutes and 1 minute for Level 4 and Level 5, respectively.

Figure 4 shows the average values of the maximum evacuation time for Level 4 and Level 5 over 20 replications for all the combinations. Due to the HLF rule (discussed in section 3.2.1), patients on Level 5 always have the dominant priority to occupy the shared elevator E_1, making the evacuation rarely dependent on the allocation on Level 4 (see Figure 4b). The results of the maximum evacuation time of Level 5 show that distributing the patients to two elevators can reduce the evacuation time by decreasing the queues. For the cases where all the patients are assigned to the same elevator (i.e., when $A_5 = 000$), the evacuation takes 55.1 minutes on average. When $A_5 = 111$, it takes slightly longer time (56.2 minutes on average) due to the overall longer travel distance to E_1. When looking at the allocation of individual groups, it is observed that, with the allocations of $G_{1,5}$ and $G_{2,5}$ fixed, assigning $G_{3,5}$ to $E_{0,5}$ always reduces the evacuation time. For example, the average evacuation time of $A_5 = 110$ is 52.6 minutes, 6.4% less than that of $A_5 = 111$. It is due to the much less travel distance from G_3 to $E_{0,5}$ than to E_1. On the other hand, with the allocation of $G_{3,5}$ fixed, assigning $G_{1,5}$ and $G_{2,5}$ to different elevators reduces the evacuation time (e.g., $A_5 = 010$ and $A_5 = 100$ is takes less time than $A_5 = 110$). This is because the medical staff join the



(a) (b)

Figure 4: Maximum evacuation times for trolley-ridden patients at Level 4 and Level 5 using different elevator allocations, respectively. The boarded values are the maximum evacuation times for both levels. The overall margins of error with 95% confidence intervals are given.

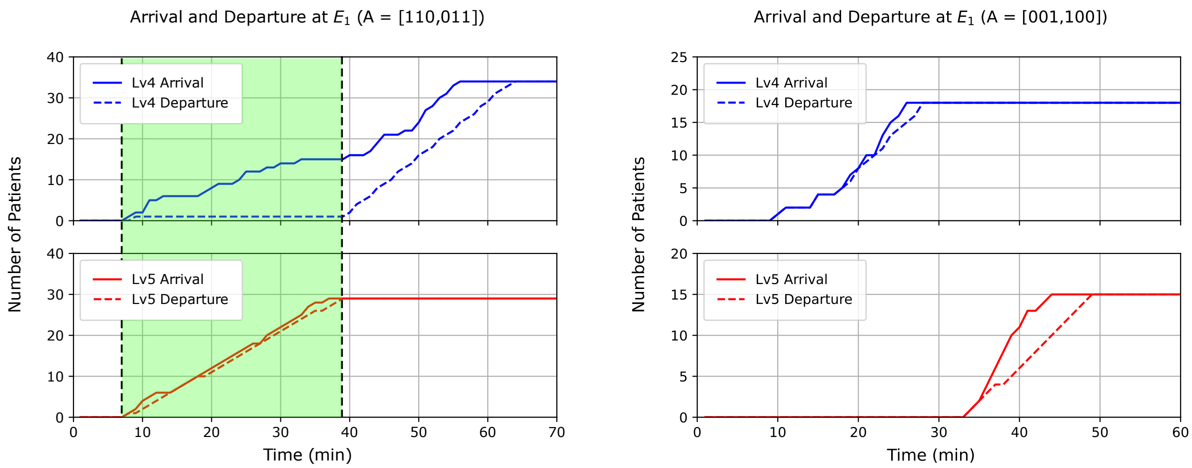
transfer process after completing the preparation for all the patients, leading to an increased departure of the patients. In this case, assigning $G_{1,5}$ and $G_{2,5}$ to different elevators will distribute the patients to two queues and therefore reduce the queuing time. Among the combinations, the best allocation is $A_5 = 010$ which takes only 49.9 minutes on average.

Similarly on Level 4, distributing patient groups to both elevators reduces the evacuation time. However, the evacuation of Level 4 is more sensitive to the allocation on Level 5 (see Figure 4a), except for the cases where all the Level 4 patients are using the exclusive elevator $E_{0,4}$ (i.e., $A_4 = 000$). In the worst case $A = [111, 111]$, where all the patient groups were assigned to the same elevator, the evacuation took 93.7 minutes and 56.0 minutes on Level 4 and Level 5, respectively. On the other hand, the best allocation $A = [000, 110]$ took only 38.2 minutes to complete the evacuation on Level 4 but 55.1 minutes on Level 5. In fact, the evacuation performance largely depends on the overlapping utilization of the shared elevator E_1 by the patient groups. The overlap slows down the evacuation because the Level 4 patient groups have to wait for the clearance of the queue on Level 5 as a result of the HLF rule. A bad example is the evacuation with $A = [110, 011]$, taking 64.2 minutes on Level 4 and 52.4 minutes on Level 5, due to the huge overlap of the utilization of E_1 from 9 to 39 minutes (see Figure 5a). On the contrary, the good practice $A = [001, 100]$ (the optimal allocation) generated no overlap (see Figure 5b) and evacuated the patients in 39.6 minutes and 49.6 minutes on Level 4 and Level 5, respectively. Other examples with overall evacuation time less than 50 minutes can be found where the overlap of utilization is less likely to happen (e.g., $A = [000, 100]$ and $[000, 101]$).

4.3 Discussion

The above case study showed the shortest evacuation time required in a given specific patient distribution, rescue team size, and fire location. Note that the underlying model is agent-based and is able to reflect the navigation behaviors of individuals as well as their interactions (i.e., potential congestion at bottlenecks can be revealed in the simulation). A bad allocation leads to not only less efficient elevator usage, but also higher risks of congestion in the hallways, resulting increased evacuation time (Reader may refer to our previous study (Su et al. 2021) for details).

A limitation of the study is that the patients are sparsely grouped regarding their locations for simplicity. The allocations can be refined by considering smaller group units or individual patients using optimization methods such as genetic algorithm (Haghpanah and Foroughi 2018). From the manpower perspective, the



(a) (b)

Figure 5: Arrival and Departure at E_1: (a) an example of bad allocation $[110,001]$ and (b) an example of good allocation $[001,100]$. The green area indicates the overlap of utilization by patient groups on both levels.

ED managers may consider increasing the number of medical staff on duty and the rescue team size to further reduce the evacuation time. The results also suggest a need for varying the evacuation method, e.g., transferring patients to wheelchairs to save the elevator capacity or to stretchers which can be moved through staircases. Note that the intention is to show the ability of the model to provide numerical results for optimizing vertical evacuation strategy for trolley-ridden patients under particular situations. The experimental results and conclusion can be different when the scenario setup is changed.

5 CONCLUSION AND FUTURE WORK

In this paper, we present an evacuation model for analyzing evacuation elevator allocation for trolley-ridden patients in multi-level hospital emergency departments. The model consists of behavior modeling of trolley-ridden patients, medical staff, and rescuers. A novel evacuation elevator model and corresponding boarding and alighting behavior of passengers were introduced to resolve the unrealistic congestion in front of elevator lobbies. As a case study, the model was applied to evaluate the elevator allocation in a two-level scenario of the future ED of Singapore General Hospital (SGH). The model is able to suggest the best solution to the minimum evacuation time on both levels. The experimental results reveal that evacuation of the upper level is rarely dependent on the lower level, while the evacuation of the lower level is more sensitive to the allocation on the upper level mainly because of the overlapping utilization of the shared elevator by both levels.

The presented model can be extended to different scenarios other than evacuation elevator allocation analysis. In fact, we have conducted numerical experiments for optimizing rescue team size on each level of the department. Ambulant pedestrians evacuating through staircases can also be included in the future to simulate the evacuation of a more complex scenario. One limitation, however, is the lack of validation on the model due to the limited existing literature. To address the issue, mock-up experiments or real-world observations at the hospital should be considered for data collection in the future.

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REFERENCES

Abdelghany, A., K. Abdelghany, H. Mahmassani, and W. Alhalabi. 2014. "Modeling framework for optimal evacuation of large-scale crowded pedestrian facilities". *European Journal of Operational Research* 237(3):1105–1118.

Andrée, K., D. Nilsson, and J. Eriksson. 2016. "Evacuation experiments in a virtual reality high-rise building: exit choice and waiting time for evacuation elevators". *Fire and Materials* 40(4):554–567.

Boyce, K., T. Shields, and G. Silcock. 1999, Feb. "Toward the Characterization of Building Occupancies for Fire Safety Engineering: Capabilities of Disabled People Moving Horizontally and on an Incline". *Fire Technology* 35(1):51–67.

Butler, K., E. Kuligowski, S. Furman, and R. Peacock. 2017. "Perspectives of occupants with mobility impairments on evacuation methods for use during fire emergencies". *Fire Safety Journal* 91:955–963.

Cai, W., S. Zhou, M. Low, F. Tian, H. Seah, D. Ong, V. Tay, B. Hamilton, L. Luo, D. Wang, K. Sornum, M. Lees, Z. Shen, D. Chen, X. Xiao, A. Liang, and M. Xiong.. 2010, 07. "COSMOS: CrOwd Simulation for Military OperationS". Technical report, School of Computer Eng., Nanyang Technological University, Singapore.

Chen, Y., C. Wang, J. Yap, H. Li, H. Hu, C. Chen, and K. Lai. 2020, Jun. "Fire Evacuation Process Using Both Elevators and Staircases for Aging People: Simulation Case Study on Personnel Distribution in High-Rise Nursing Home". *Discrete Dynamics in Nature and Society* 2020:5365126.

Curtis, S., B. Zafar, A. Gutub, and D. Manocha. 2013. "Right of Way: Asymmetric Agent Interactions in Crowds". *Visual Computer* 29(12):1277–1292.

Daganzo, C. F. 1997. "Cumulative plots". In *Fundamentals of Transportation and Traffic Operations*. Bingley: Emerald Group Publishing Limited.

Department for Communities and Local Government 2009. *Guidance on the emergency use of lifts or escalators for evacuation and fire and rescue service operations*. London, UK: Department for Communities and Local Government.

Elevator Community Wiki 2022. "The one minute standard". https://elevatorcommunity.fandom.com/wiki/The_One_Minute_Standard, accessed 10th April 2022.

Geoerg, P., J. Schumann, S. Holl, and A. Hofmann. 2019, Jun. "The Influence of Wheelchair Users on Movement in a Bottleneck and a Corridor". *Journal of Advanced Transportation* 2019:9717208.

Gladyshev, P., and A. Patel. 2004. "Finite state machine approach to digital event reconstruction". *Digital Investigation* 1(2):130–149.

Golmohammadi, D., and D. Shimshak. 2011, 11. "Estimation of the evacuation time in an emergency situation in hospitals". *Computers & Industrial Engineering* 61:1256–1267.

Gutierrez-Milla, A., F. Borges, R. Suppi, and E. Luque. 2015. "Crowd Evacuations SaaS: An ABM Approach". *Procedia Computer Science* 51:473–482.

Haghpanah, F., and H. Foroughi. 2018. "Optimal Shelter Location-Allocation during Evacuation with Uncertainties: A Scenario-Based Approach". *arXiv preprint arXiv:1802.05775*.

Helbing, D., and P. Molnár. 1995, May. "Social force model for pedestrian dynamics". *Phys. Rev. E* 51:4282–4286.

Hunt, A., E. Galea, and P. Lawrence. 2015. "An analysis and numerical simulation of the performance of trained hospital staff using movement assist devices to evacuate people with reduced mobility". *Fire and Materials* 39(4):407–429.

Jafari, M., D. Golmohammadi, and K. Seyed. 2008. "Staff Management in Emergency Evacuation Preparedness and Response". *Journal of Homeland Security and Emergency Management* 5(1).

Klein, G. 1997. "The Recognition-Primed Decision (RPD) Model: Looking Back, Looking Forward". *Naturalistic Decision Making*:285–292.

Kurdi, H., S. Al-Megren, R. Althunyan, and A. Almulifi. 2018. "Effect of exit placement on evacuation plans". *European Journal of Operational Research* 269(2):749–759.

Kwak, J., M. Lees, W. Cai, A. Pourghaderi, and M. Ong. 2021, Feb. "Estimating horizontal movement performance of patient beds and the impact on emergency evacuation time". *Safety Science* 134:105038.

Mielczarek, B., and J. Uziałko-Mydlikowska. 2012. "Application of computer simulation modeling in the health care sector: a survey". *SIMULATION* 88(2):197–216.

Moussaïd, M., N. Perozo, S. Garnier, D. Helbing, and G. Theraulaz. 2010. "The walking behaviour of pedestrian social groups and its impact on crowd dynamics". *PLoS One* 5(4):e10047.

NHS England 2021. "NHS England Emergency Preparedness, Resilience and Response (EPRR) Planning for the Shelter and Evacuation of people in healthcare settings". https://www.england.nhs.uk/ourwork/eprr/, accessed 1st February 2021.

SCDF 2021. "Singapore Civil Defence Force - Community and Volunteers". https://www.scdf.gov.sg/home/community-volunteers, accessed 10th April 2022.

Sorsa, J., H. Ehtamo, J.-M. Kuusinen, M. Ruokokoski, and M. Siikonen. 2018, Jan. "Modeling uncertain passenger arrivals in the elevator dispatching problem with destination control". *Optimization Letters* 12(1):171–185.

Strating, N. 2013. "Evacuation of bedridden building occupants". Master's thesis, Eindhoven University of Technology, The Netherlands.

Su, B., P. Andelfinger, D. Eckhoff, H. Cornet, G. Marinkovic, W. Cai, and A. Knoll. 2019. "An Agent-Based Model for Evaluating the Boarding and Alighting Efficiency of Autonomous Public Transport Vehicles". In *Computational Science – ICCS 2019*: Springer International Publishing.

Su, B., P. Andelfinger, J. Kwak, D. Eckhoff, H. Cornet, G. Marinkovic, W. Cai, and A. Knoll. 2020. "A passenger model for simulating boarding and alighting in spatially confined transportation scenarios". *Journal of Computational Science* 45:101173.

Su, B., J. Kwak, A. Pourghaderi, M. Lees, K. Tan, S. Loo, I. Chua, J. Quah, W. Cai, and M. Ong. 2021. "A Model-Based Analysis of Evacuation Strategies in Hospital Emergency Departments". In *Proceedings of the Winter Simulation Conference*, WSC '21: IEEE Press.

Taaffe, K., R. Kohl, and D. L. Kimbler. 2005. "Hospital evacuation: issues and complexities". In *Proceedings of the Winter Simulation Conference, 2005.*, edited by M. E. Kuhl, N. M. Steiger, F. B. Armstrong, and J. A. Joines, 943–950. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Wang, J., L. Zhang, Q. Shi, Y. P., and X. Hu. 2015. "Modeling and simulating for congestion pedestrian evacuation with panic". *Physica A: Statistical Mechanics and its Applications* 428:396 – 409.

Wei, Q., L. Wang, Y. Liu, and M. M. Polycarpou. 2020. "Optimal Elevator Group Control via Deep Asynchronous Actor–Critic Learning". *IEEE Transactions on Neural Networks and Learning Systems* 31(12):5245–5256.

Yokouchi, M., Y. Hasegawa, R. Sasaki, R. Gaku, Y. Murata, N. Mizuno, A. Inaba, and T. Tanaka. 2017. "Operations analysis of hospital ward evacuation using crowd density model with occupancy area and velocity by patient type". In *2017 Winter Simulation Conference (WSC)*, edited by W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer, and E. Page, 2984–2993. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

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