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RESEARCH ARTICLE

Help Me Evacuate! A Smart Adaptable Evacuation System With Congestion Prediction Capabilities

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ABSTRACT Emergency evacuation planning is a vital problem that affects building occupants' safety. The commonly used static evacuation plans rely on static signs disregarding crowd density changes. Such static plans often lead to congestion at emergency exits; since many occupants tend to avoid following exit signs as they feel safer following the crowds exiting the building or following other paths familiar to them. This paper proposes a smart and adaptable evacuation system that predicts congestion and adapts accordingly to minimize evacuation time. We introduce a simulation model that mimics occupants' movement in different building layouts. The proposed system performs Monte Carlo simulations to forecast possible congestion locations and guide occupants away from them. Guiding directions are displayed and updated to consider dynamic environment changes. We evaluated our approach compared to a greedy evacuation method that relies on static exit signs, showing a significant evacuation time improvement of 21% achieved on average by our approach.

INDEX TERMS Congestion forecasting, Monte Carlo simulations, smart evacuation.

I. INTRODUCTION

Efficient emergency evacuation protocols are crucial for complex environments that suffer from crowds, such as hospitals, governmental agencies, and others. In such complex layouts, the shortest paths are not always the fastest ones in evacuation scenarios due to possible congestion that is likely to happen [1], [2]. In addition, occupants are not expected to be familiar with layout architecture nor aware of exit locations; thus, some may panic, causing congestion. Classical evacuation plans in such crowded and complex environments may lead to congestion causing several casualties. Accordingly, adaptive evacuation protocols that forecast potential future congestion will help guide occupants to avoid routes that lead to such congestion. Thus, such adaptive protocols will significantly decrease the evacuation time and thus minimize the number of casualties.

Classical pre-determined evacuation plans only consider the shortest paths to exits, assuming that following such paths by crowds would lead to the shortest evacuation times. However, in real life, especially in large-scale evacuations, such plans cannot predict possible congestion that may occur at exits as depicted in Figure 1. Furthermore, such plans cannot adapt and react efficiently to possible panic scenarios that may prevent occupants from following the pre-determined plans. For example, in large-scale evacuations, panic causes occupants to rush out with crowds and ignore exit signs, thus causing congestion in specific regions that cannot be mitigated via pre-determined evacuation plans. Besides, the heterogeneous population distribution slows evacuation, as not all exits are efficiently utilized. Therefore, all of this combined highlights the need to find an approach that efficiently utilizes the building layout and exits.

This paper proposes a novel smart evacuation guidance system that adapts to various real-world scenarios to resolve congestion and minimize evacuation time. In other words, our evacuation guidance model predicts future trajectories of occupants following a Monte Carlo scheme to forecast possible congestion and generate guiding exit directions via electronic sign boards that can be updated remotely. It is worth mentioning that we assume occupants' locations are

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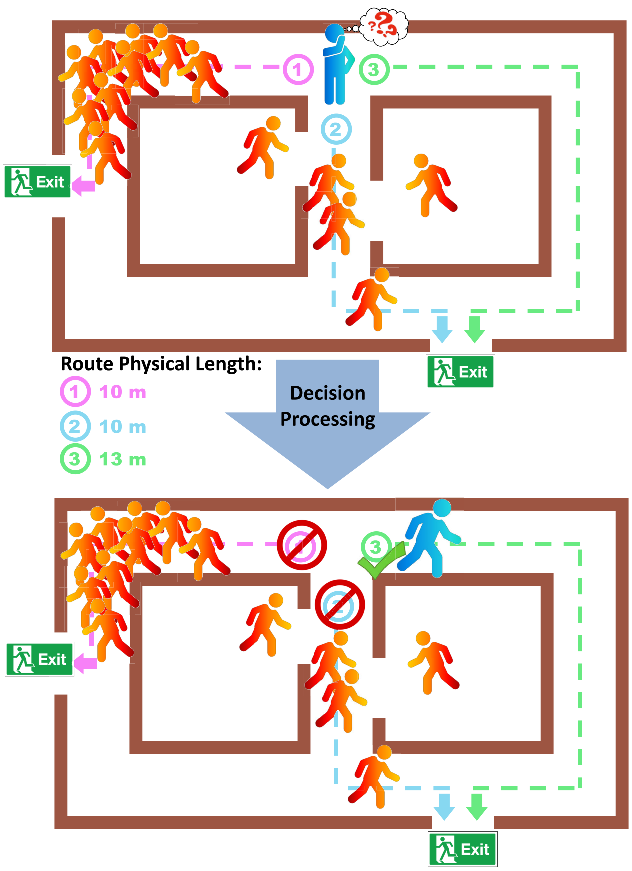


FIGURE 1. **Shortest paths are not always the fastest ones in evacuation scenarios due to possible congestion.**

given via installed tracking and motion capture systems in the considered environment. All in all, our approach considers factors of population densities, paths' physical lengths, and escape flow rates of exits and thus finds an appropriate combination of the aforementioned factors in developing evacuation route plans. The main paper contributions can be summarized as follows:

- recommending least congested routes to highly dense populations in large-scale architecturally complex building layouts,
- performing evacuation planning based on the forecasted state of the evacuation situation, and
- modeling occupants' movements.

Furthermore, we evaluated our approach in simulation using complex environments that mimic real-world scenarios to ensure the effectiveness of our system. Additionally, we compared our approach to a classical greedy evacuation approach that relies on existing static exit signs to highlight our contribution. Our experiments demonstrate a significant improvement in reducing evacuation time.

The rest of the paper is organized as follows. Section II gives a brief on the recent research work concerned with emergency evacuation modeling. Section III breaks down and discusses the system framework in detail. Section IV present three case study experiments and discusses their results. Section V presents conclusions and makes future recommendations.

II. RELATED WORK

Emergency evacuation modeling has received increasing attention in the last few years as a replacement for costly and time-consuming real-life evacuation drills. Recent research has considered different aspects of emergency evacuation modeling, such as population movement and architectural influence on evacuation. Others have considered the impact of population emotions and behaviors, besides discussing evacuation route selection and smart evacuation guidance systems.

Movement modeling approaches differ concerning their primary focus. For example, microscopic systems model population movement with a high level of detail, tracking their spatiotemporal status. Microscopic modeling systems include approaches that model movements as a result of internal and external social forces of neighboring occupants [1], [3], [4], [5], [6]. Additionally, other microscopic methods model occupants as autonomous and communicating agents who make decisions based on their characteristics, other agents, or the environment [7], [8], [9], [10], [11]. Moreover, microscopic methods include models that discretize space to cellular grids and time to time-steps [12], [13], [14], [15], [16], [17]. On the other hand, macroscopic models trade off accuracy for computational complexity. Common macroscopic methods are network-based models that discretize environments into networks of nodes and arcs. Such nodes and arcs have specified capacities and occupants propagating as flows with a certain speed through the network [18], [19], [20].

Furthermore, several research studies have investigated the influence of emotions and behaviors on evacuation [9], [21], [22]. For instance, emotions such as panic, fear, stress, and anxiety significantly impact people's decisions in emergencies. Additionally, people communicate together and exchange knowledge during evacuation scenarios, affecting their decisions. For example, Han and Liu [3] model occupants' willingness to follow neighbors who provide information. Additionally, Liu et al. [23] investigated the effect of group leaders on evacuation.

Moreover, route selection is a complex decision that involves many variables, including architectural data accuracy, hazard conditions, and population density topography. Therefore, research studies considered combinations of such variables to reach a decision [5], [24], [25], [26], [27]. For instance, Wang et al. [24] rely on a fire dynamics simulator to model fire development to recommend escape routes. Besides, Liu et al. [5] compute a fitness function for exits considering congestion as a factor.

Additionally, architectural design can be a driving factor in decision-making. Therefore, some researchers considered the influence of architectural design on evacuation outcomes concerning the number of rooms, room sizes, exit sizes, and exit arrangements to give design suggestions [8], [28].

TABLE 1. Comparison between smart evacuation guidance system features.

Reference	Dynamic Signage	Guiding Personnel / Mobile Devices	Iterative Route Updating	Detailed Congestion Forecasting
Our proposed approach	✓	✗	✓	✓
Samah [30]	✓	✗	✗	✗
Cho *et al.* [31]	✓	✗	✗	✗
Galea *et al.* [32]	✓	✗	✗	✗
Bernardini *et al.* [33]	✓	✗	✓	✗
Kim *et al.* [34]	✓	✗	✓	✗
Ferraro and Settino [35]	✓	✗	✓	✗
Nguyen *et al.* [36]	✓	✗	✗	✗
Khalid *et al.* [37]	✗	✓	✗	✗
Jiang [38]	✗	✓	✓	✗
Balboa *et al.* [39]	✓	✗	✓	✗
Fu and Liu [40]	✓	✗	✓	✗
Xu *et al.* [41]	✓	✗	✓	✗
Berceanu *et al.* [42]	✓	✗	✗	✗

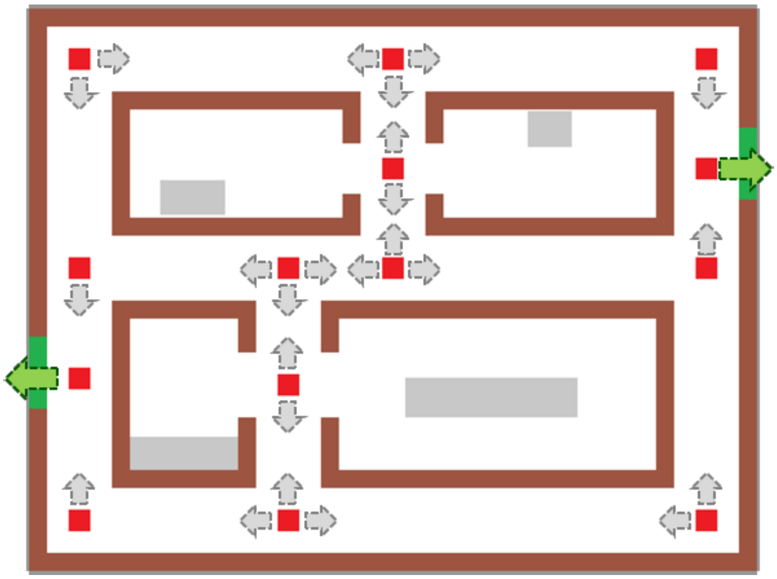


FIGURE 2. Sample layout. Red elements represent visual signs, green elements represent exits, reddish brown elements represent walls and grey elements represent obstacles.

Furthermore, Caliendo et al. [29] considered finding architecturally non-invasive evacuation plans to preserve existing architecture, which is crucial for historical buildings [29].

As for smart evacuation guidance systems, they are relatively novel in research; however, the number of research studies has significantly increased in the past few years. Most existing research works employ Internet of Things (IoT) components to collect data, such as individual locations and hazard conditions [32], [34], [37], [39], [41], [42]. Then, this data is used to assess emergencies, develop a suitable evacuation plan, and display rerouting updates via dynamic signage systems.

Several smart evacuation approaches focus only on recommending the safest evacuation routes by eliminating routes associated with hazardous areas and recommending the best-remaining alternatives. For instance, Samah et al. [30] propose a modification to Dijkstra's algorithm so that it eliminates hazardous nodes to provide the shortest and safest paths. Then, Cho et al. [31] update directions of dynamic exit signs to avoid hazard locations. After that, Ferraro and Settino [35] optimize routes by discretizing layouts as nodes and weighted edges to avoid fire relying on IoT devices. Furthermore, Jiang [38] uses the ant colony algorithm to optimize escape routes by calculating effective lengths of alternative routes in terms of sensor-monitored fire status, which is continuously updated and indicated to occupants through a GIS-based mobile device. Furthermore, Fu and Liu [40] propose a BIM-based graph network of nodes and path lines using the work of Fu et al. [43] to represent paths of any polygon-shaped room correctly. Then, they determine optimal evacuation routes in terms of length and accessibility to show recommended and negated sign directions. Also, Xu et al. [41] add a parameter to the route selection probability of ant colony algorithm, which

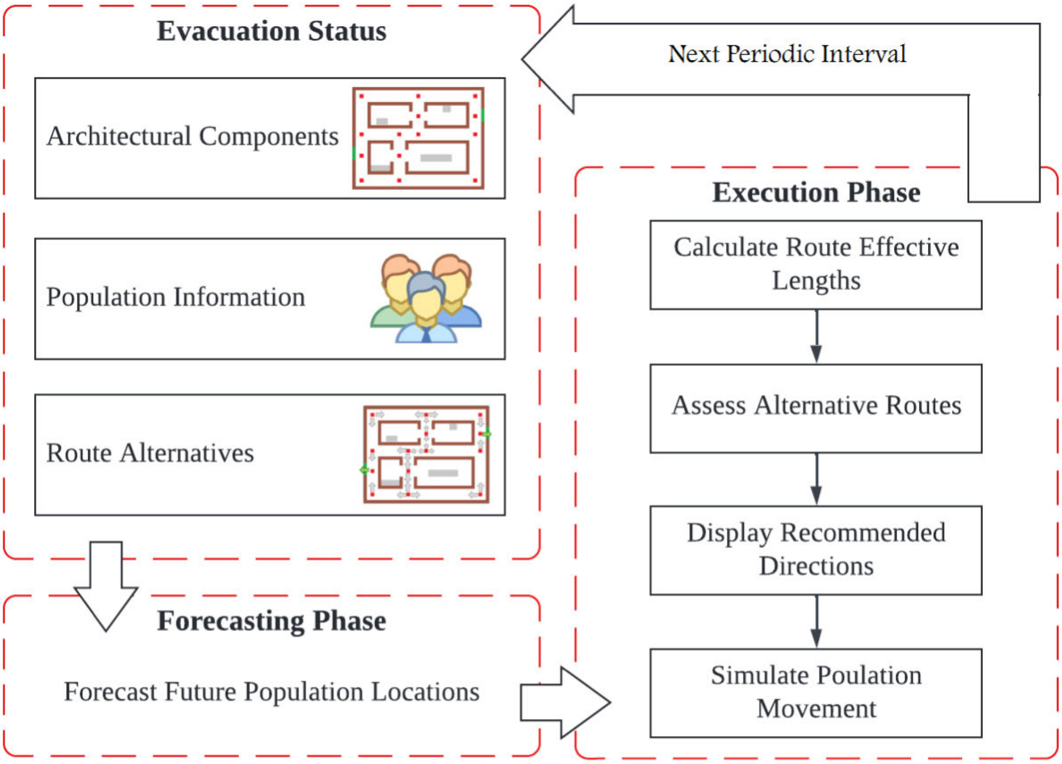


FIGURE 3. System flow.

takes fire conditions into consideration to penalize hazardous paths and avoid them. Additionally, Berceanu et al. [42] propose a decentralized agent-based model that uses a guidance control system, which weights paths according to fire conditions to compute the shortest and safest paths using Dijkstra's algorithm. However, such strategies turn out to be a greedy shortest-path strategy after making hazardous areas inaccessible. Accordingly, path planning strategies have the most significant effect on evacuation efficiency for such approaches.

Additionally, some approaches consider other decision model parameters rather than focusing only on path length. For instance, Bernardini et al. [33] adopt a microscopic approach that accounts for crowd density besides recommending the shortest path. They wait until any region across the recommended route reaches its full capacity to eliminate that route and recommend another one. Thus, this approach, even though it considers crowd density, also tends to follow a greedy scheme that does not foresee upcoming congestion, which turns such an approach to finding the shortest path among the available routes. Furthermore, they only consider a low occupancy scenario whose full capacity is only 800 occupants, unlike the high occupancy scenario of about 10,000 occupants, as in our case. It is worth mentioning that microscopic approaches fit better to low occupancy scenarios [10], [23], [25], [39]. On the other hand, Nguyen et al. [36] adopt a macroscopic approach that accounts for crowd density by representing the evacuation building as a network of cross-connected floor sub-graphs where they weight edges according to route length, capacity, density, and hazard conditions. Edges representing route segments are weighted individually, assembled, and evaluated globally to attain the shortest routes. However, as discussed earlier, such a macroscopical representation misses the movement details of the occupants. Therefore, comparing this network-based approach or any macroscopic approach in general with our microscopic approach would not be fair or realistic since macroscopic approaches do not account for delays due to congestion or obstacles. Moreover, Balboa et al. [39] consider pre-evacuation delays due to the time needed for perception and collecting belongings before starting evacuation. They run stochastic simulations following the work of Cuesta et al. [44] to estimate evacuation time for alternative routes based on hazard locations and dynamically update sign directions accordingly. Hence, they introduce a decision model that eliminates hazardous routes and calculates total evacuation time as the sum of pre-evacuation and route travel times. Thus, this method also turns out to be a greedy shortest-path strategy after eliminating hazardous routes.

As opposed to the current smart evacuation systems that cannot foresee and resolve setbacks during the evacuation process, this paper proposes a novel efficient approach that forecasts evacuation congestion based on microscopic simulation level. In other words, our approach recommends the actual fastest routes for evacuation, not just the shortest routes in terms of path length as in the case of greedy approaches. Our approach performs Monte Carlo simulations to forecast occupants' future positions and plan accordingly to avoid congestion. Furthermore, we update evacuation route plans based on our periodic predictions and guide the occupants via dynamic signage. Additionally, We model dense crowds in architecturally complex environments to overcome the lack of such a combination in microscopic approaches. In other words, our approach models occupants' movements in a microscopic scheme to retain necessary congestion details; however, we perform routing decisions on a macroscopic level to scale up to complex environments. In Table 1, we compare the features of the discussed smart evacuation guidance systems and our proposed approach. Our approach performs congestion forecasting without relying on guiding personnel or mobile devices, i.e., mobile devices for guiding occupants. Additionally, our approach periodically updates the recommended routes based on congestion status.

III. SMART EVACUATION ADAPTABLE SYSTEM FRAMEWORK

In this section, we introduce our novel Monte-Carlo-based smart evacuation guidance system. Our model relies on forecasting occupants' movement, then, based on such forecasts, it generates guidance decisions that are used to simulate experimental evacuations, as shown in Figure 3. In this section, we first define how we model evacuation environments and occupants' movements. After that, we discuss how we perform congestion forecasting. Then, we show how we calculate the effective routes recommended to occupants during evacuation execution.

A. ENVIRONMENT AND MOVEMENT MODELING

We consider single-storey buildings for this work, where we model them as grid maps similar to the sample layout shown in Figure 2, with annotated locations of exits (green elements) and guiding visual signs (red elements). Furthermore, we map each grid cell to the closest guiding sign since it affects the evacuation decision of people occupying that cell. Besides, we assume that a multi-object tracking system is deployed on the property's existing surveillance cameras, which provide our evacuation system with occupants' locations.

We simulate occupants' movement on that grid map in discrete time steps. Each occupant occupies some grid cells according to their size. Furthermore, occupants can move in any of the eight possible directions (Moore's neighborhood), as shown in Figure 4, as long as such cells have no obstacles or have enough space for that occupant. Furthermore, each occupant has a separate evacuation velocity that governs their motion across their individual paths at each time step. Such a velocity may differ according to the occupant's gender and age. Additionally, occupants who enter a congested path slow down or stop moving until there is space for them to move. Moreover, our forecasting module recommends for each occupant the fastest route according to their current location. In the rest of this section, we show how the forecasting module calculates the fastest routes.

B. MOTION FORECASTING

We perform Monte Carlo simulations of occupants' evacuation behavior as they move across the grid map to forecast population density distribution as time proceeds during evacuation. The forecasted density distribution will manifest possible congestion locations. Therefore, we sample an average evacuation speed v_e from a normal distribution, to be adopted by all occupants during the forecasting phase to mimic reality as much as possible, as shown in Equation 1:

$$v_e \sim N(\mu_e, \sigma_e), \tag{1}$$

where μ_e and σ_e refer to the average evacuation speed and its standard deviation, respectively.

Although adopting an average speed for all occupants adds more uncertainty to the prediction results, it mimics available information during real evacuation scenarios since it is not realistic to track the individual speeds of the occupants during evacuation and perform predictions based on them. Note that we consider this unified average velocity only for the forecasting purpose to have a realistic model; however, we assign an individual velocity for each occupant during simulating the evacuation execution, as we will show in Section III-D.

Additionally, we model occupants' adherence to following recommended evacuation directions of our guidance system using a normal distribution to sample the percentage of committed occupants, as shown in Algorithm 1. Then, we uniformly sample the occupants' behavior based on that sampled percentage, i.e., determine the committed occupants in our forecast based on uniform selection among the pool of occupants based on the sampled percentage. To perform conservative forecasting, we assume that most occupants will follow a greedy strategy heading toward the closest exit regardless of the guiding signals. Accordingly, we simulate occupants' motion along their selected routes according to the sampled average evacuation speed for a specific forecasting horizon to predict their future locations.

C. EFFECTIVE PATHS

At the end of each forecasting horizon, we utilize the forecasted locations of occupants to recommend efficient paths for the occupants in evacuation execution. For each occupant, based on their location, we calculate an effective path length of all possible paths leading to a possible exit of the building storey, instead of the known physical path lengths. Then, we recommend the path with the least effective length. The effective path length l^* corresponds to weighting the physical path length l_p with a congestion factor f_c, to account for possible delays due to congestion, as follows:

$$l^* = f_c \times l_p. \tag{2}$$

We compute the congestion factor for each path considering path occupancy based on the predicted population density

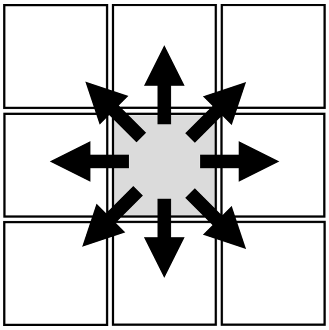


FIGURE 4. Moore's neighborhood.

and exit flow rate along that specific path. The intuition behind such a factor relies on the fact that travel time through congestion will significantly increase as it becomes governed by exit flow rate instead of evacuation speed, especially for highly dense crowds. In other words, we assume that occupants will walk a distance denoted by l_e on a path of length l_p, where $l_p \geq l_e$, following an evacuation velocity v_e until they encounter congestion. Then, for the rest of the path length, i.e., $l_p - l_e$, occupants slow down as enforced by the exit flow rate. Therefore, we assume that path travel time is a summation of travel time for free walking and travel time through congestion. Each travel time is considered separately in order to avoid duplication, as follows:

$$t^* = \frac{l_e}{v_e} + \frac{occ}{flow}, \tag{3}$$

where t^* denotes total evacuation time, while *occ* represents the number of occupants flowing along that path, and *flow* corresponds to the exit flow rate of the occupants along that path. Furthermore, we empirically assume that the free walking distance is a proportional fraction of the physical path length relative to occupants' density, as follows:

$$l_e = l_p - density \times l_p. \tag{4}$$

Moreover, we assume that path evacuation time can be alternatively considered as a function of the sought congestion factor, path physical length, and evacuation velocity, as follows:

$$t^* = f_c \times \frac{l_p}{v_e}. \tag{5}$$

Therefore, considering Eq. 3, Eq. 4 and Eq. 5, we can derive the congestion factor as follows:

$$f_c = 1 - density + \frac{v_e}{l_p} \times \frac{occ}{flow}. \tag{6}$$

D. SIMULATED EVACUATION

We rely on simulation to evaluate the evacuation performance based on the recommended directions since real-world drills are costly and cannot be extensively performed. Occupants start moving according to a speed sampled from a normal distribution. In this evaluation phase, we sample an individual speed for each occupant based on their gender and age

Algorithm 1 Forescasting of Occupants' Future Locations

Input: $Occupants$, $Routes_{recommended}$, $Routes_{greedy}$
Output: $Occupants$

$Adherence\ \% \sim N(\mu_{adherence}, \sigma_{adherence})$
for $o \in Occupants$ **do**
  $X \sim U(0, 1)$
  if $(X \leq Adherence\ \%)$ **then**
    $ComplyingOccupuants.append(o)$
  end if
end for
for $t = 0$ to $ForecastingHorizon$ **do**
  for $o \in Occupants$ **do**
    if $(o \in ComplyingOccupuants)$ **then**
      $o \leftarrow move(v_e, Routes_{recommended}(o))$
    else
      $o \leftarrow move(v_e, Routes_{greedy}(o))$
    end if
  end for
end for

following the work of Chu et al. [45]. In this evaluation phase, as opposed to the forecasting phase, having a specific velocity for each occupant is more realistic. Furthermore, unlike the forecasting phase, we assume that most occupants follow the guiding signals, compared to those who may panic and follow a greedy strategy heading toward the closest exit regardless of the guiding signals. We simulate occupants' motion and their compliance with the recommended routes, as shown in Algorithm 1, except that there is no forecasting horizon.

IV. EXPERIMENTAL RESULTS

We evaluated our model on complex environments in simulations since large-scale real-life evacuation drills would be costly, difficult to organize, time-consuming, inflexible, and, most importantly, they would risk the safety of participants. In this section, we explore the simulation environments used, besides discussing our experimental settings and assumptions. Additionally, we discuss the evaluation metrics used to evaluate our model. Finally, we illustrate our findings and analyze our model's performance.

A. SIMULATION ENVIRONMENTS

We used three case studies to validate the performance of our model in recommending evacuation guidance plans. All three case studies take place in hospitals, as they are considered architecturally complex buildings occupied by large numbers of staff members, patients, and visitors who may not be familiar with such environments' floor plans. The adopted case studies are the ground floors of RIAU University Hospital in Pekanbaru, Indonesia (Figure 5); Mongar Regional Referral Hospital in Mongar, Bhutan (Figure 6); and Hospital General Benito Juarez in Michoacán, Mexico (Figure 7). We represent the environments' maps as cellular grids with a resolution of 30 cm. Additionally,

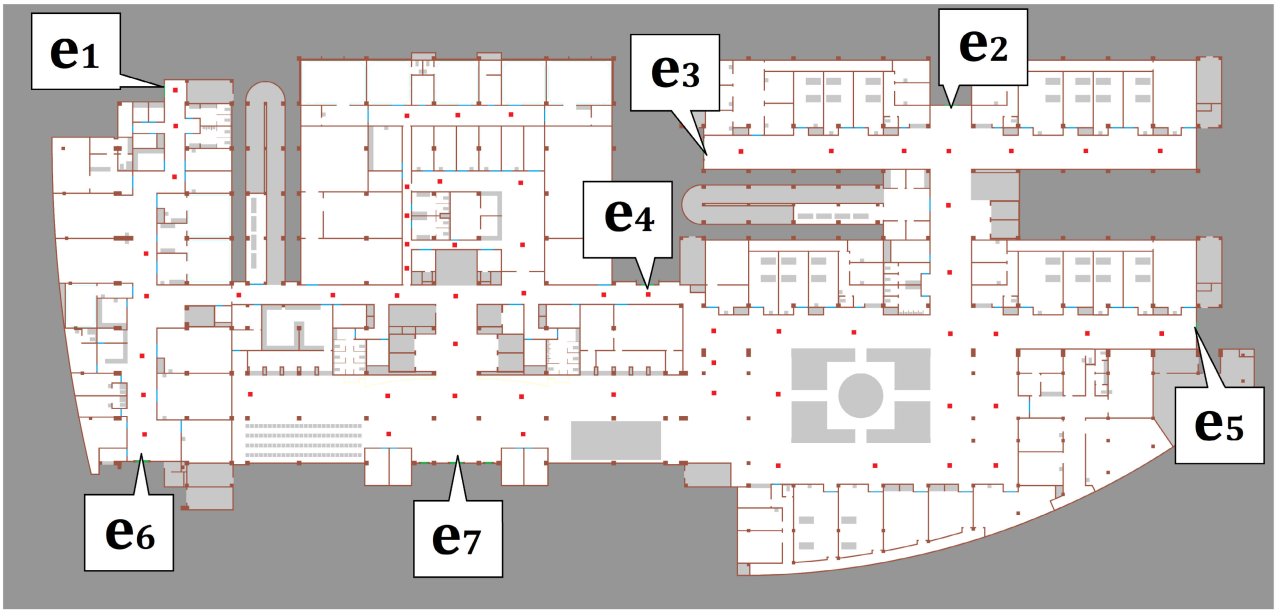


FIGURE 5. RIAU University Hospital layout emphasizing exit locations.

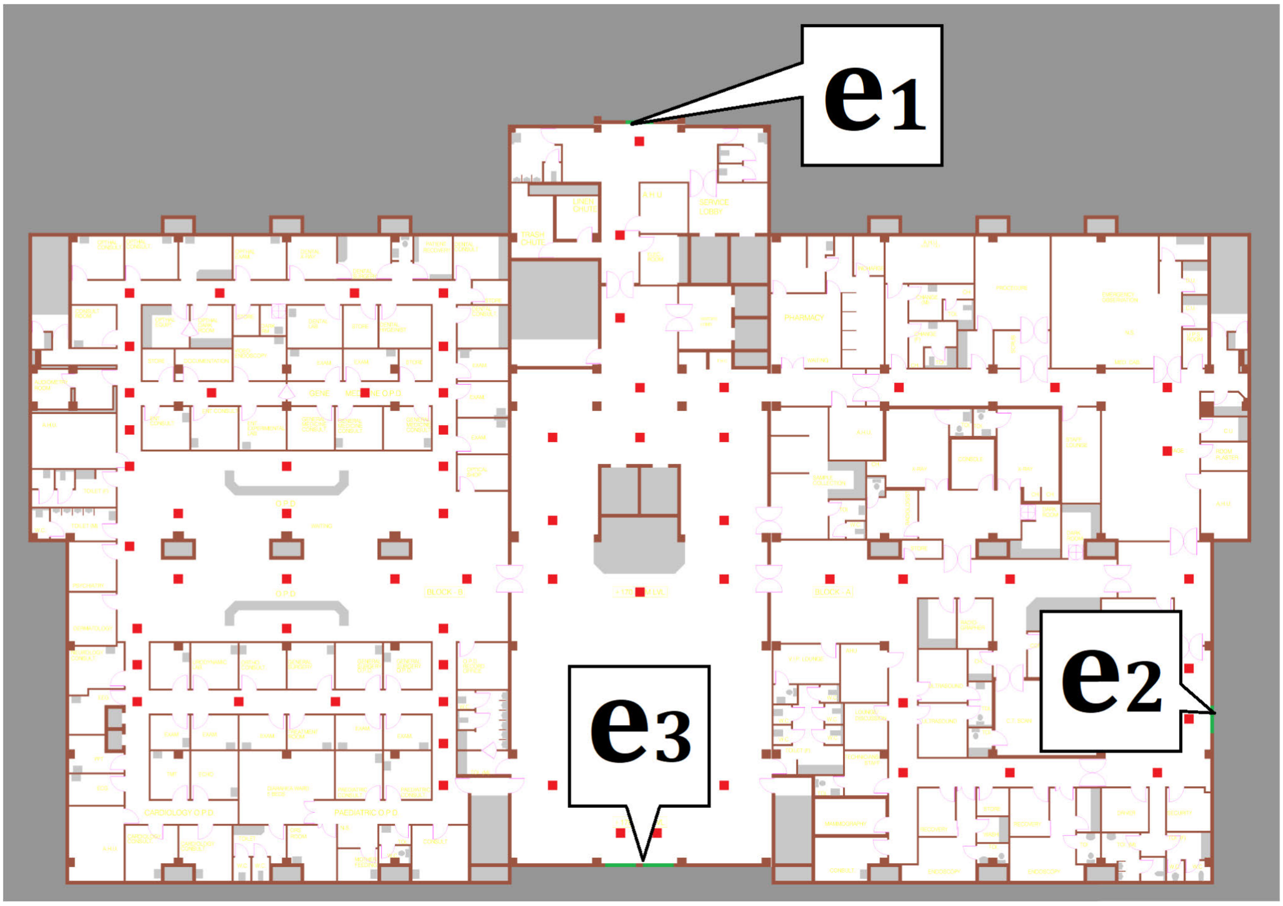


FIGURE 6. Mongar Regional Referral Hospital layout emphasizing exit locations.

we model occupants as squares of 60 cm in length. RIAU University Hospital's layout has a 5694 m^2 free area and seven exits, while Mongar Regional Referral Hospital has a 2557 m^2 free area and three exits. However, Hospital General Benito Juarez has a 3950 m^2 free area and five exits.

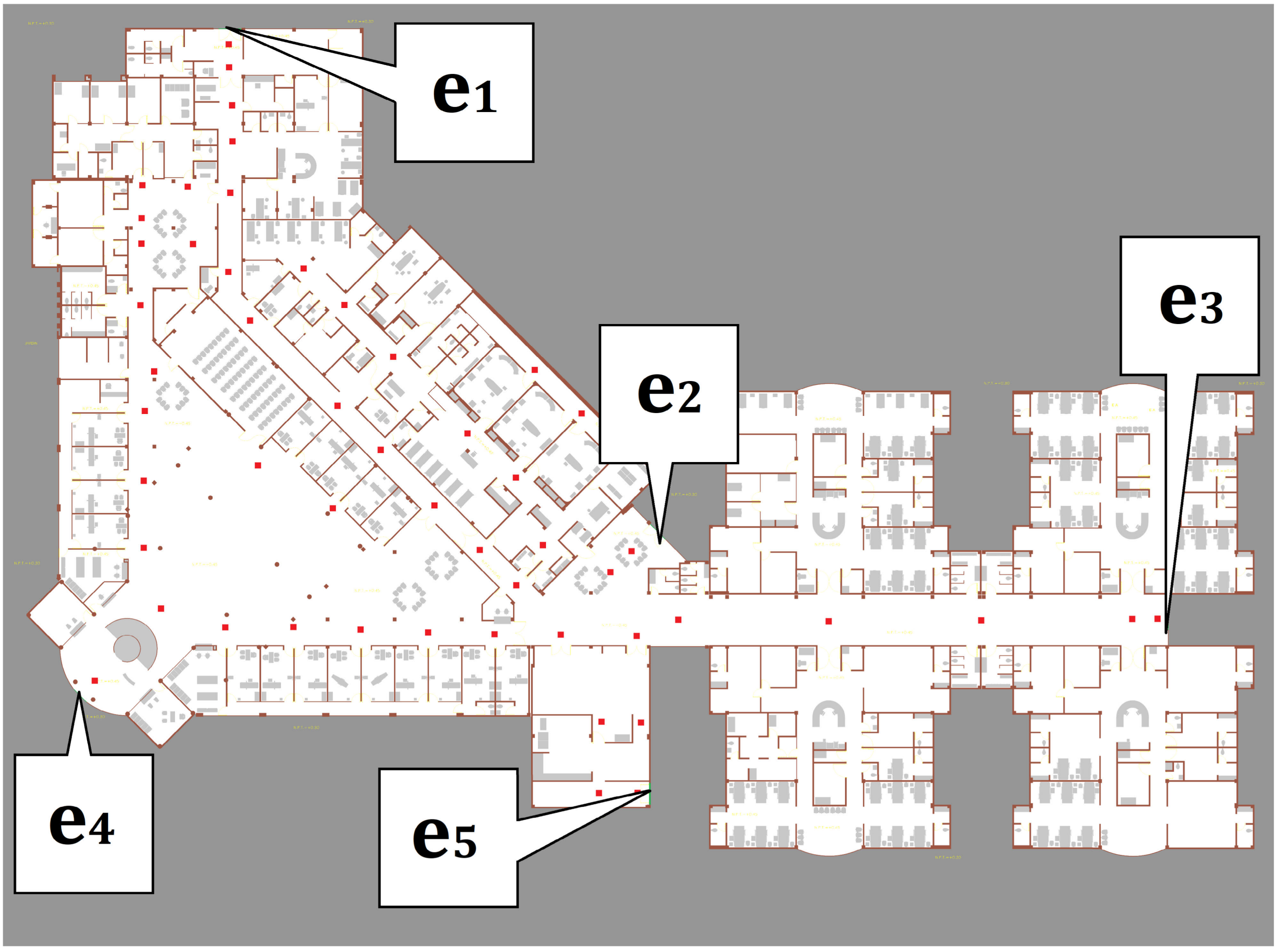


FIGURE 7. Hospital General Benito Juarez layout emphasizing exit locations.

TABLE 2. Average evacuation time of 50 simulation runs on RIAU University Hospital and improvement percentage compared to greedy evacuation.

# Occupants	Approach		Avg. evacuation time (sec) ↓	Improvement (%) ↑
3000	Greedy		438	-
	Single Prediction		423.4	3.33%
	Periodic Prediction	30 s	**372.68**	**14.91%**
		60 s	375.88	14.18%
5000	Greedy		705.96	-
	Single Prediction		666.36	5.61%
	Periodic Prediction	30 s	632.48	10.41%
		60 s	**622.8**	**11.78%**

TABLE 3. Average evacuation time of 50 simulation runs on Mongar Regional Referral Hospital and improvement percentage compared to greedy evacuation.

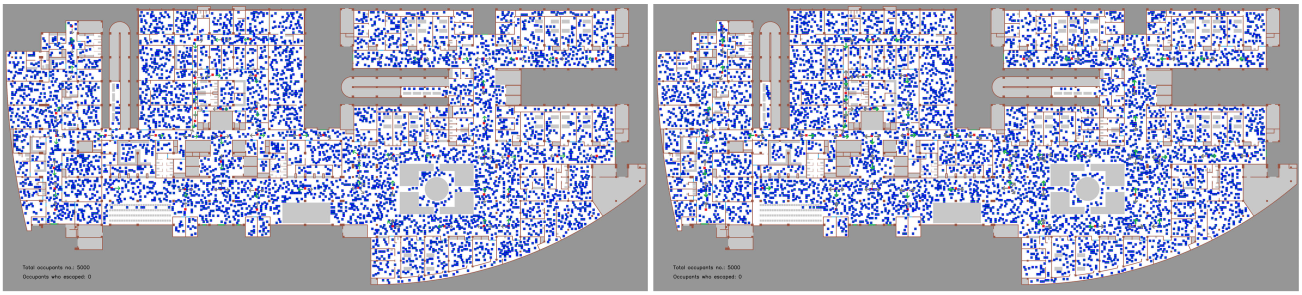
# Occupants	Approach		Avg. evacuation time (sec) ↓	Improvement (%) ↑
3000	Greedy		616.88	-
	Single Prediction		790.60	-28.2%
	Periodic Prediction	30 s	**543.88**	**11.8%**
		60 s	545.76	11.5%
5000	Greedy		1041.76	-
	Single Prediction		1358.84	-30.44%
	Periodic Prediction	30 s	**927.76**	**10.94%**
		60 s	941.44	9.63%

B. EXPERIMENTAL SETTINGS

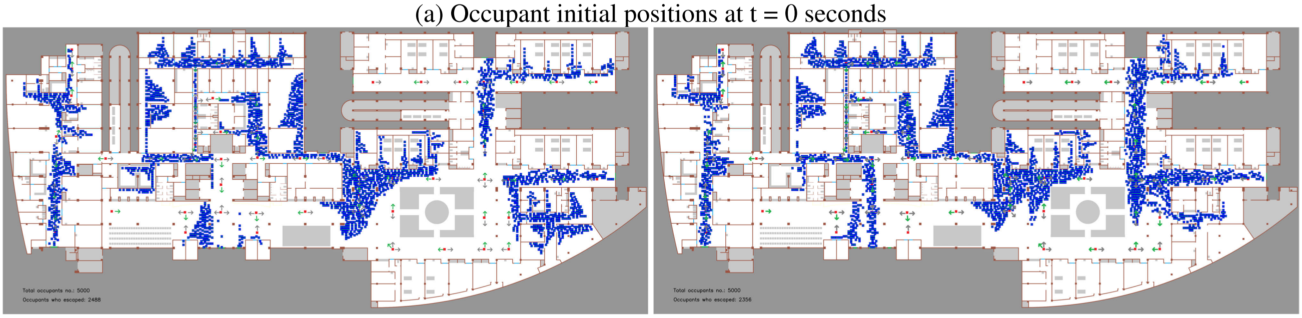
We perform simulations assuming that occupants' current locations and velocities are given to our model via motion capture systems instead of real-life drills. Additionally, we assume that population velocities follow normal distributions for the execution phase with a mean of 1.287 m/s for men, 1.243 m/s for women and 1.09 m/s for elders [45], and a standard deviation of 0.5 m/s. As for the forecasting phase, we assume that all occupants adopt a crowd average velocity to account for the uncertainty of each occupant's velocity. Furthermore, we model occupants' trust behavior by assuming that the majority of the population will comply with our system-recommended evacuation directions. We use a normal distribution with a sampled average of 70% of the population and a standard deviation of 15% for committed occupants.

C. EVALUATION METRICS

We compare our proposed approach to a greedy evacuation method. Considering that the greedy approach is the benchmark, we consider an approach to be efficient if its average evacuation time is shorter than that of the greedy. Furthermore, we consider a variant of our approach, which performs a single forecast at the beginning of the simulation,

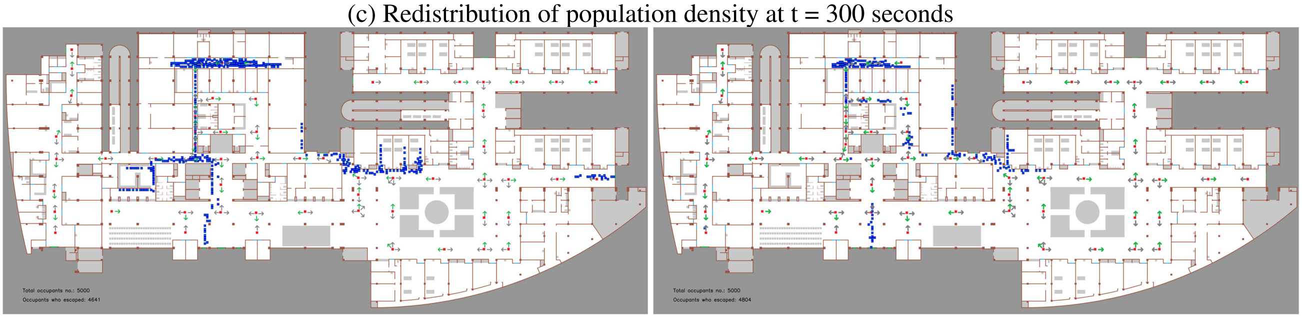


(a) Occupant initial positions at t = 0 seconds



(b) Congestion display at t = 150 seconds

(c) Redistribution of population density at t = 300 seconds



(d) Only 3.9% of the population is left to evacuate for the prediction approach, while 7.2% is left for the greedy approach run at t = 450 seconds

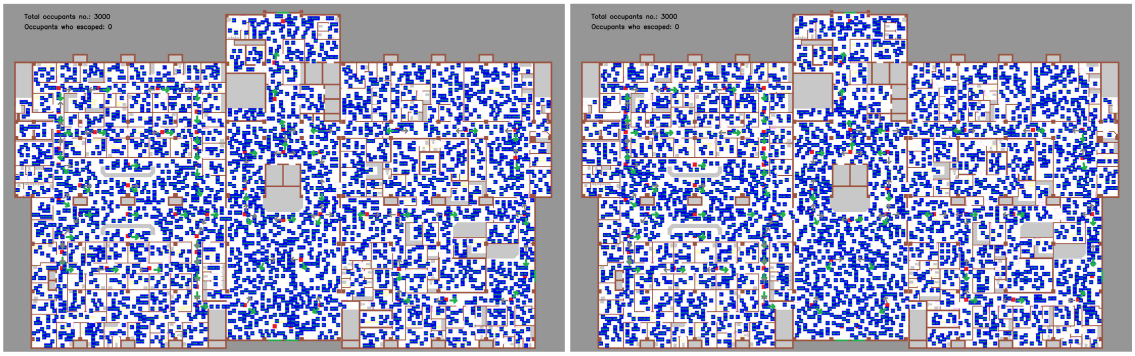
FIGURE 8. Analysis of a greedy run on the left and a periodic prediction (per 30 seconds) run on the right at t = 0, 150, 300, and 450 seconds for RIAU University Hospital.

as opposed to our proposed periodic forecasting, resulting in a static plan based on an averaged population density distribution. The purpose of comparing our approach to such a variant is to evaluate the effect of the proposed periodic forecasting on evacuation time. Furthermore, we compare the utilization percentage of environments' exits to evaluate the congestion reduction.

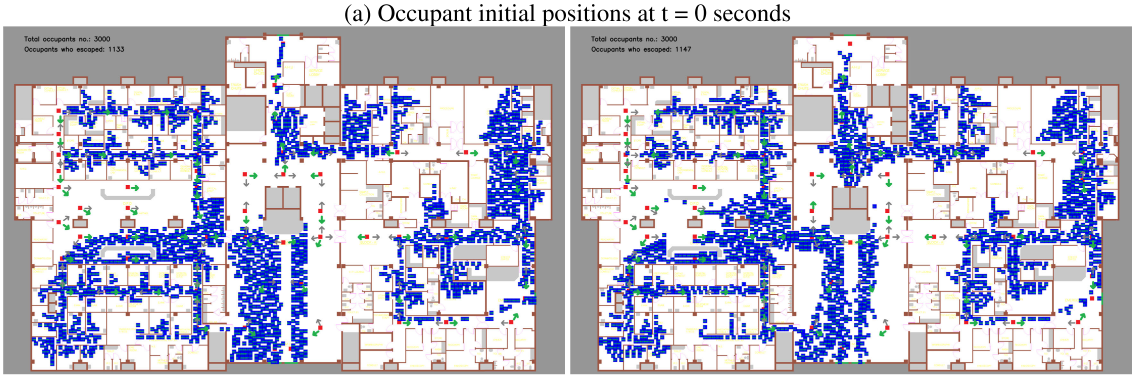
It is worth mentioning that most existing smart evacuation systems, as discussed in Section II, turn out to be equivalent to greedy approaches relying on shortest-path finding after they eliminate the unsafe routes. Therefore, relying on the greedy approach as a benchmark is reasonably sufficient. Also, comparing our microscopic approach to any of the network-based macroscopic approaches mentioned in Section II will not be fair or realistic since they do not account for delays due to congestion or obstacles.

D. SIMULATION RESULTS

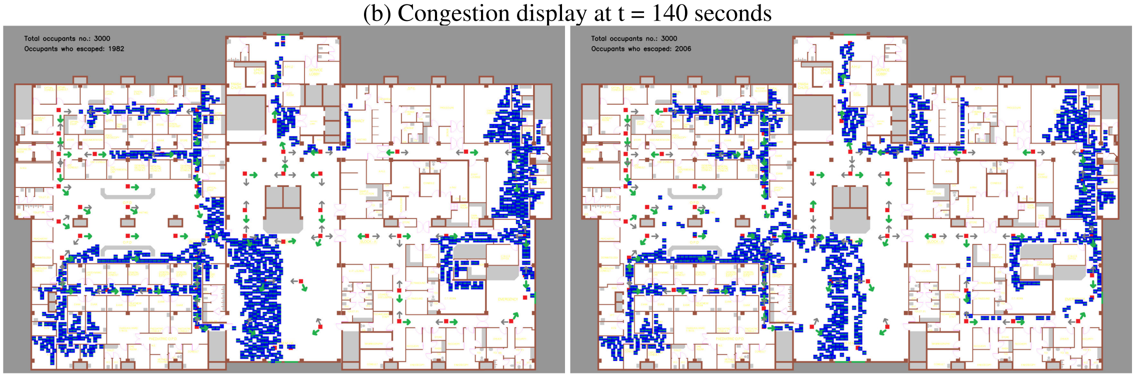
We evaluated our approach using different population densities to assess the performance in the considered case studies



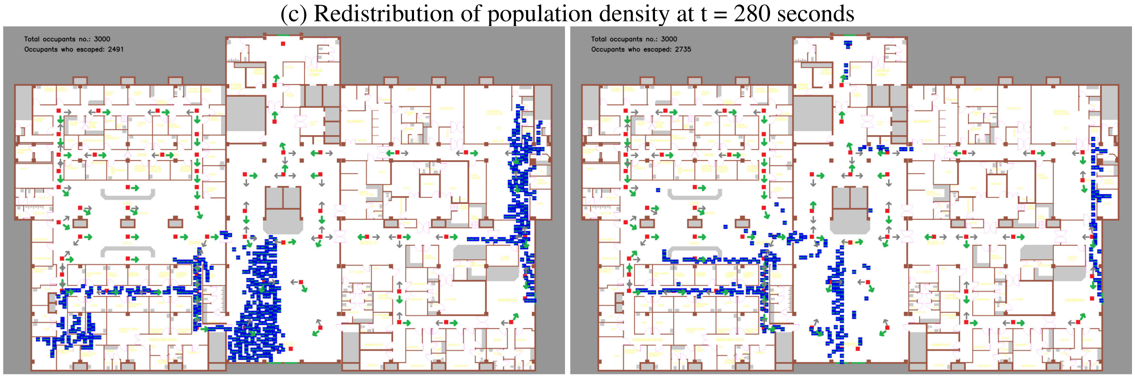
(a) Occupant initial positions at t = 0 seconds



(b) Congestion display at t = 140 seconds



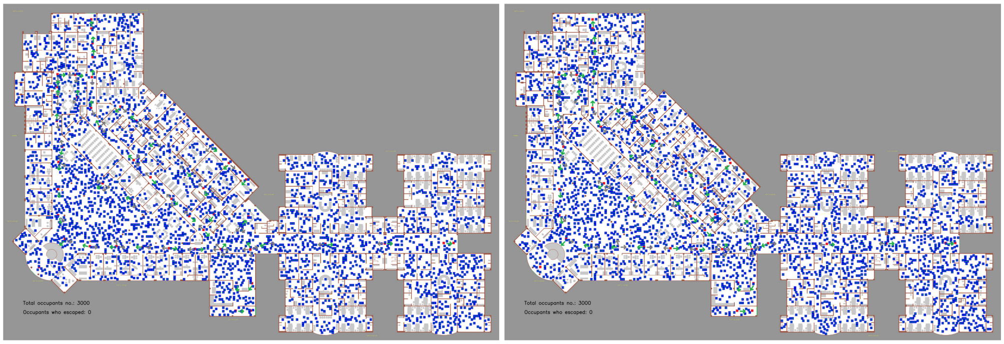
(c) Redistribution of population density at t = 280 seconds



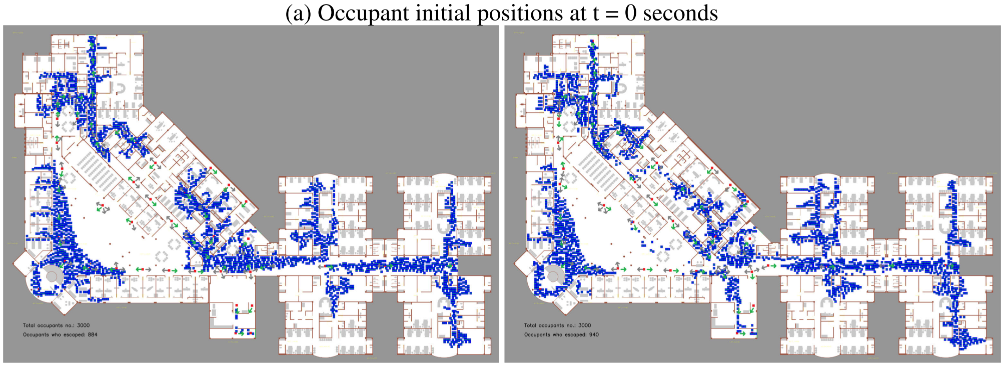
(d) Only 8.8% of the population is left to evacuate for the prediction approach, while 16.9% is left for the greedy approach run at t = 420 seconds

FIGURE 9. Analysis of a greedy run on the left and a periodic prediction (per 30 seconds) run on the right at t = 0, 140, 280, and 420 seconds for Mongar Regional Referral Hospital.

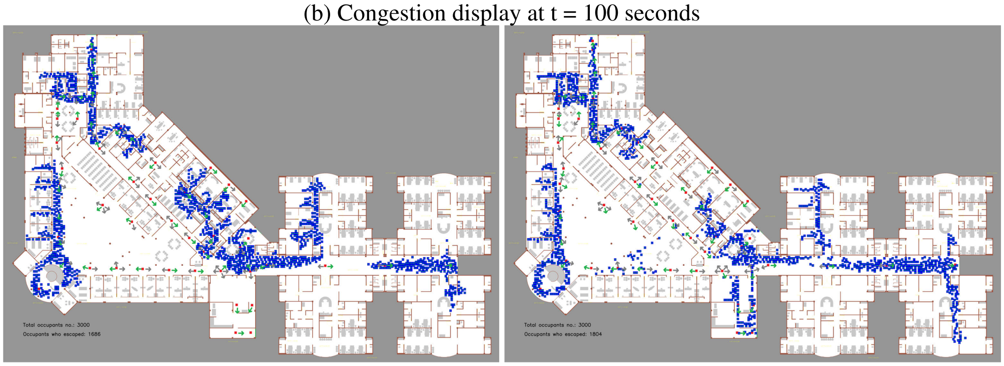
for moderate and overcrowded densities. Furthermore, we considered two forecasting horizons: 30 and 60-second intervals. It is also worth mentioning that such forecasting horizons are intuitive since shorter horizons will lead to an oscillating performance, while longer ones will lead to a slow response to potential rapid changes in evacuation



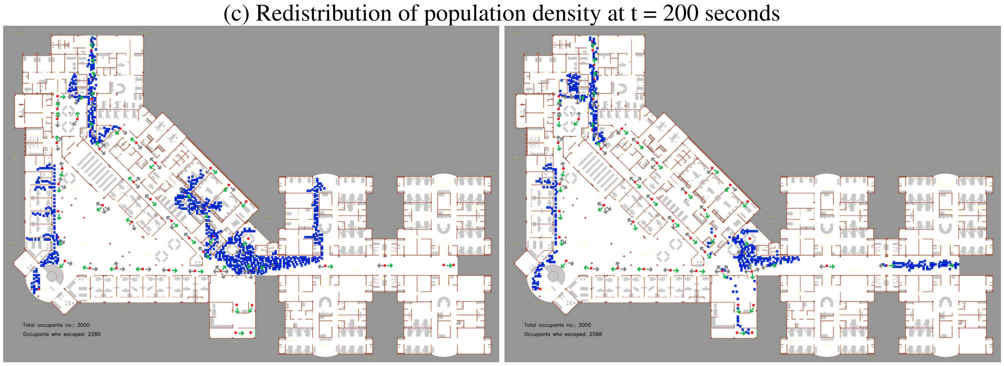
(a) Occupant initial positions at t = 0 seconds



(b) Congestion display at t = 100 seconds



(c) Redistribution of population density at t = 200 seconds



(d) Only 14.4% of the population is left to evacuate for the prediction approach, while 24% is left for the greedy approach run at t = 300 seconds

FIGURE 10. Analysis of a greedy run on the left and a periodic prediction (per 60 seconds) run on the right at t = 0, 100, 200, and 300 seconds for Hospital General Benito Juarez.

scenarios. Moreover, we performed 50 independent runs of our simulations for each case study to alleviate the randomness effect.

As for the evacuation time improvement compared to the greedy approach, our approach with periodic prediction significantly overcomes both greedy and single forecast approaches for all case studies, as shown in Tables 2, 3 and 4. As demonstrated, the average time improvement for all case studies of our periodic forecasting approach ranges from 21.29% to 21.56% for the 30 seconds and 60 seconds

TABLE 4. Average evacuation time of 50 simulation runs on Hospital General Benito Juarez and improvement percentage compared to greedy evacuation.

# Occupants	Approach		Avg. evacuation time (sec) ↓	Improvement (%) ↑
3000	Greedy		693.6	-
	Single Prediction		510.28	26.43%
	Periodic Prediction	30 s	420.36	39.39%
		60 s	**415.68**	**40.07%**
5000	Greedy		1151.24	-
	Single Prediction		833.59	27.59%
	Periodic Prediction	30 s	687.72	40.26%
		60 s	**665.32**	**42.21%**

TABLE 5. Comparison between exit utilization in the Greedy and Periodic Prediction approaches, and percentage of exit utilization change for RIAU University Hospital.

Exit	Approach		△ Utilization (%)
	Greedy	Prediction	
e_1	6.8%	6.8%	0.0%
e_2	15.8%	20.6%	4.8%
e_3	3.9%	3.9%	0.1%
e_4	26.2%	24.5%	-1.7%
e_5	14.5%	11.9%	-2.6%
e_6	8.8%	10.4%	1.6%
e_7	24.2%	22.0%	-2.2%

TABLE 6. Comparison between exit utilization in the Greedy and Periodic Prediction approaches, and percentage of exit utilization change for Mongar Regional Referral Hospital.

Exit	Approach		△ Utilization (%)
	Greedy	Prediction	
e_1	15.8%	19.2%	3.4%
e_2	28.2%	26.0%	-2.2%
e_3	56.0%	54.8%	-1.2%

TABLE 7. Comparison between exit utilization in the Greedy and Periodic Prediction approaches, and percentage of exit utilization change for Hospital General Benito Juarez.

Exit	Approach		△ Utilization (%)
	Greedy	Prediction	
e_1	20.3%	20.9%	0.6%
e_2	26.6%	15.5%	-11.2%
e_3	26.0%	30.2%	4.2%
e_4	23.0%	21.7%	-1.2%
e_5	4.1%	11.7%	7.6%

forecasting horizons, respectively. Furthermore, the superior performance of our periodic forecasting approach takes place for both moderate and heavy occupancy levels. Additionally, as opposed to our approach, which can adapt to environments of various sizes, the single forecast approach fails to provide mature guidance for evacuation in small environments with a limited number of exits, as in the Mongar Regional Referral Hospital case study. Moreover, it is worth mentioning that varying the forecasting horizon from 30 seconds to 60 seconds will not cause a significant effect since it improves the evacuation time by just 0.28% on average.

E. CONGESTION AND EXITS UTILIZATION ANALYSIS

Furthermore, our approach improves utilization percentages of the exits of our case studies' environments. In other words, our approach balances the distribution of occupants heading to the exits taking into account minimizing the evacuation time. Such balance in distributing occupants across exits leads to a decrease in the congestion of occupants instead of having them concentrated around specific exits compared to others.

For instance, for RIAU University Hospital, with a 5000 occupant population, Figure 8 shows snapshots taken at different time steps comparing a greedy run and a periodic prediction run of 30 seconds prediction horizon with evacuation times close to those of their averages, i.e., 706 and 630 seconds, respectively. At t = 150 seconds, exits e_2 and e_6 have a better utilization in the periodic prediction approach than in the greedy approach, the congestion at e_4 somewhat decreased and occupants are more uniformly distributed around e_7. Furthermore, at t = 300 seconds, e_2 is still being utilized in the prediction approach and masses of occupants heading to e_5 in the greedy approach have already cleared in the prediction approach. Additionally, at t = 450 seconds, the prediction approach run is left with 196 occupants to evacuate, while the greedy approach run still has 359 occupants trying to evacuate.

Similarly, for Mongar Regional Referral Hospital with a 3000 occupant population, Figure 9 demonstrates that e_1 has a better utilization in our periodic prediction approach at t = 140 seconds, and congestion at e_3 slightly decreases. At t = 280 seconds, e_3 does not suffer anymore from congestion, as opposed to the greedy approach, and occupants heading towards that exit are more uniformly distributed using our prediction approach. Finally, at t = 420 seconds, congestion has almost cleared, and all three exits are still being utilized in our prediction approach with 265 occupants to evacuate. On the other hand, congestion persists for the greedy approach run, and 509 occupants are trying to evacuate using two exits only.

Also, for Hospital General Benito Juarez, with a 3000 occupant population, Figure 10 shows that at $t = 100$ seconds, e_3 and e_5 are better utilized using our periodic prediction approach than in the greedy approach, and e_2 is congestion relieved. At $t = 200$ seconds in the prediction approach, e_2 is no longer congested, and e_5 is still being utilized, whereas it is not in the greedy approach. Finally, at $t = 300$ seconds, all five exits are still being utilized in the prediction approach run with 432 occupants to evacuate, while the greedy approach run utilizes three exits only and still has 720 occupants to evacuate.

Finally, we demonstrate the change in exit utilization percentages in Tables 5, 6, and 7 for RIAU Hospital, Mongar Hospital, and Benito Juarez Hospital, respectively. We show that the utilization percentage of some exits has decreased to reduce congestion along the paths leading to them, such as e_7 in RIAU Hospital, e_3 in Mongar Hospital, and e_2 in Benito Juarez Hospital. Additionally, the utilization of other exits has increased to accelerate the evacuation, such as e_2 in RIAU Hospital, e_1 in Mongar Hospital, and e_5 in Benito Juarez Hospital.

V. CONCLUSION AND FUTURE WORK

This paper introduces a novel evacuation guidance system that can dynamically guide highly dense populations in architecturally complex buildings. We apply a Monte Carlo simulation model to forecast future congestion periodically to guide occupants away from highly congested areas and minimize evacuation time. We evaluated our model via simulation using three complex case studies, i.e., RIAU University Hospital, Mongar Regional Referral Hospital, and Hospital General Benito Juarez. We demonstrated that our approach leads to a significant reduction in evacuation time that ranged from 21.29% to 21.56% on average based on the prediction horizon compared to the greedy evacuation approach. Additionally, we demonstrated that our approach distributes evacuees as uniformly as possible across any building layout to make the most efficient use of it.

As for future work, we aim to address several enhancement aspects. For instance, we plan to extend our model to handle multi-storey buildings. Accordingly, we need to model evacuation on stairs and the dynamics of descending crowds down a building, as parameters governing movement down staircases, such as velocity, differ from those of horizontal movement. We aim to test the influence of congestion formation along stairs on evacuation performance by simulating occupant accumulation moving down from one storey to another. Moreover, we will utilize a fire model to simulate fire conditions and their progress across a building to consider fire danger factors when calculating the route direction decision plan. Thus, we plan to test different fire breakout scenarios at different building locations. Also, a safe distance from fire needs to be defined while considering fire progress. Any route that does not maintain the defined safe distance will be eliminated from the evacuation plan. Finally, we plan to automate dynamic signs placement. We intend to explore methods to identify all possible decision locations where dynamic signs should be installed without redundancy. For instance, corridor intersections and room doors are considered appropriate decision locations; however, only one sign should be placed within a certain radius to avoid confusion. In open areas, signs should be placed within a certain distance to prevent occupants from getting lost and to help them keep track of the evacuation routes.

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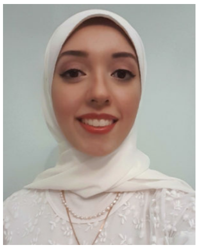

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