Optimizing Shelter Site Locations in Residential Community: A Geo-Simulation and Genetic Algorithm Approach

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ABSTRACT

As disasters, both natural and human-induced, grow more frequent, effective sheltering and evacuation become crucial. While existing studies considered approaches optimizing shelter location by simulating individuals' evacuation behaviors, most rely on pre-determined functions and overlook the heterogeneity of individuals' behaviors. To address this limitation and account for the complexities of residents' evacuation processes, we develop an approach that integrates Agent Based Modeling (ABM) with a Genetic Algorithm (GA), using the evacuation simulation results from ABM to optimize community shelter locations. We validate the proposed method by simulating residents' evacuation in an assumed nighttime earthquake event within a student residential community in Shenzhen. This study provides a tool assisting in the optimization of community shelter locations in pre-disaster planning.

Keywords

Community-level shelter location, Geo-Simulation, Scenario planning, Agent-based modeling, Genetic Algorithm, Community resilience

INTRODUCTION

In recent years, the increasing frequency of natural and man-made disasters has place human communities under greater risks. n response, emergency managers and community planners have sought innovative strategies to mitigate these risks. A critical component of such strategies is disaster evacuation, which aims to quickly relocate affected populations to safe locations. Effective evacuation planning is essential, particularly in emergencies where time is limited and large populations are involved. One key aspect is the optimization of shelter site locations, which directly influences evacuation efficiency (Zhao et al., 2017). Existing studies on shelter site optimization refers to spatial accessibility (e.g., Liu et al., 2011; Choi et al., 2020) or utilizes weighted multi-criteria decision approaches (e.g., Trivedi, 2018; Zhang et al., 2019). For example, Hosseini et al. (2022) employed a multi-criteria approach to obtain the suitability distribution of shelters. However, such studies frequently fall short in capturing how shelter locations impact actual evacuation time. To address this, some researchers have employed GIS-based models or traffic simulations to determine optimal shelter placement.

Community-level evacuation is often a complex process that includes both indoor and outdoor evacuation. It requires consideration of interactions among evacuees, their relationships, and the physical environment (Haghpanah et al., 2021; Chen et al., 2021; Chen et al., 2022). Particularly, during rapid nighttime evacuations, disaster perception among evacuees can vary significantly (Wong et al., 2020). Some evacuees may be in states of sleep or other deep focus, making them unable to initiate evacuation immediately. These individuals often require the assistance from others, adding to the complexity of simulating the evacuation process (Zhang et al., 2022). Macroscopic evacuation simulation methods (e.g., fluid-dynamic approaches) treat evacuees as homogeneous entities, making it difficult to capture interpersonal interactions. Therefore, more detailed simulation methods are needed to better reflect community-level evacuation behavior.

Individual-level geo-simulation methods, such as Cellular Automata, social force models, and agent-based models (ABM), have been widely used to simulate community evacuation under various disaster scenarios (e.g., Zia et al., 2013; Zhang et al., 2018; Yang et al., 2020; Gao & Wang, 2021). Among them, ABM is particularly effective in representing evacuee heterogeneity, behavioral contagion, and human-environment interactions (Aguirre et al., 2011; Wang et al., 2016; Hao et al., 2022; Chen et al., 2023). A few studies have applied ABM to shelter site planning, but some limitations remain. For example, Hashemi et al. (2013) utilized ABM to assess existing fixed shelters without identifying alternative superior locations of shelters. In an effort to consider the dynamic situations in shelter location selection, Yu et al. (2018) combined ABM with a multi-criteria approach to optimize existing shelter site locations. Liu et al. (2023) employed ABM with simulation visualization to identify and resolve shelter capacity inadequacies and community road congestion issues. While these two studies can help to add individual evacuation behaviors into shelter site planning, the optimization iterative process relies on manual experience adjustments, thus they risk missing the potential optimal combination of shelters.

Shelter location allocation models commonly integrate optimization algorithms to determine optimal shelter locations under specific objectives (e.g., Ozbay et al., 2019). These models move beyond subjective judgment by providing systematic planning solutions. However, most still overlook individual-level evacuation behaviors. Studies (e.g., Milburn et al., 2023; Shih et al., 2022) have shown that assuming evacuees always go to the nearest shelter is unrealistic, potentially undermining planning efforts through resource misallocation. Therefore, it is essential to account for both rational and irrational behaviors driven by social, environmental, and psychological factors. To address these research limitations, incorporating ABM simulation results into location-allocation optimization algorithms presents a promising direction. Given the computational complexity of ABM and the goal of identifying optimal shelter configuration, heuristic algorithms (e.g., Genetic Algorithm, or GA) may be more suitable than exact algorithms.

This study proposes a hybrid approach that integrates ABM with GA to identify optimal shelter locations while accounting for individual evacuation behaviors. We calibrated the approach on a student residential community in Shenzhen, China, simulating nighttime evacuations where student evacuee agents differ in initial evacuation states, walking speeds, and evacuation route choices. We experimented with three scenarios characterized by different evacuation time periods and community conditions. Specifically, we considered whether the evacuation starts at 0:00 or 3:00, and the likelihood of residents heading to the nearest stairwell or shelter. Our approach yield the set of shelters that minimizes the total evacuation time for the community. It reveals how dynamics in community evacuation situations affect shelter planning outcomes. The findings demonstrate the effectiveness of the proposed hybrid ABM-GA model and offer insights for enhancing community resilience through informed shelter planning.

LITERATURE REVIEW

Geo-Simulation of Human Evacuation Behavior

Disaster evacuation and sheltering is a complex process that involves both the initial evacuation decision-making and the subsequent movement of evacuees. Various methods have been developed to simulate these two critical phases. In the initial stage of evacuation, social and environmental factors significantly influence evacuation decisions (Whitehead et al., 2000). For instance, Lovreglio et al. (2015) and Zhao et al. (2020) examined how physical factors (e.g., alarm systems, building space) and social factors (e.g., group location and size) affect evacuees' evacuation status.

Both macroscopic and microscopic methods have been developed to simulate the subsequent evacuation procedure. Macroscopic approaches, such as fluid dynamics models (Henderson, 1971; Helbing et al., 1998; Hughes et al., 2002), treat evacuees as homogeneous flows, enabling large-scale modeling but failing to capture individual-level differences and interactions.

In contrast, microscopic methods model individual behaviors and interactions more precisely. Social force models simulate individuals' evacuation movements as responses to social relationships, psychological and environmental factors, i.e., the "forces" (Helbing et al., 1995; Zainuddin et al., 2010; Zhang et al., 2018). Cellular Automata (CA) can represent interactions between individuals and their environment at a local scale (Marconi et al., 2002; Helbing et al., 2003). For example, Zheng et al. (2019) used CA to simulate underground flood evacuation. Zia et al. (2013) applied CA to model urban mobility during evacuations. ABM is a micro-simulation method where autonomous agents follow individual objectives and rules, interacting with each other and the environment. ABM can capture detailed behavioral dynamics while producing macroscopic evacuation outcomes. Some scholars also used ABM for disaster evacuation simulations. For example, Nagarajan et al. (2012) developed an ABM to explore neighbor-based warning dissemination in evacuation. Yang et al. (2020) used ABM to simulate the evacuation during a rainstorm in community scale.

Shelter Site Planning at City- and Community-Level

Shelters are essential for ensuring safety and providing basic needs during disasters (Saunders, 2003). The efficiency of evacuation is closely tied to shelter location, making shelter site optimization a key concern (Sherali et al., 1991). Researchers have adopted various methods for this purpose, including survey-based approaches, multi-criteria evaluation, and location-allocation models.

Survey-based methods assess shelter suitability by incorporating factors such as distance to hazard zones, water facilities, stores, and residential areas into questionnaire design (Choi et al., 2020). Multi-criteria approaches weigh these factors to support decision-making. For example, Trivedi (2018) employed DEcision MAking Trial And Evaluation Laboratory (DEMATEL) method to evaluate how interacting factors influencing shelter location, while Hosseini et al. (2022) used Analytic Hierarchy Process (AHP) to develop an index-based model for shelter site selection. In addition, GIS tools are commonly used to generate suitability maps that reflect the physical and social appropriateness of shelter locations (Anhorn et al., 2015; Şenik et al., 2021). These maps assign suitability scores to land units, helping planners identify appropriate shelter sites. While the multi-criteria approach has the advantage of incorporating diverse factors and supports spatial analysis, it is limited in modeling dynamic evacuation processes over time (Bera et al., 2023). Therefore, some location-allocation models, combining traffic simulations and objective optimization algorithms, were developed to optimize the location of shelters (Ozbay et al., 2019; Praneetpholkrang et al., 2021). For example, Zhao et al. (2015) developed a shelter location-allocation model for earthquake evacuation using a modified Particle Swarm Optimization (PSO) algorithm.

Despite these advancements, existing studies on shelter location allocation optimization focus primarily on spatial proximity while neglecting human behaviors, such as evacuation decision-making in the initial phase and route selection during evacuation. ABM provides an opportunity incorporate human behavior impacts into community shelter planning. However, existing ABM-based studies often rely on manual trial-and-error optimization (e.g., Yu et al., 2018), which limits their ability to explore a broader solution space or adapt to diverse community conditions. Integrating ABM with heuristic optimization algorithms, such as GA, presents a promising solution. This hybrid approach enables more robust shelter planning by identifying optimal shelter configurations while accounting for dynamic, behavior-driven evacuation patterns.

METHODOLOGY

We propose an approach integrating ABM and GA to support shelter site planning in disaster-prone communities. The model architecture is depicted in **Figure 1**. This ABM component was developed using the Mesa framework (Kazil et al., 2020) and its extension Mesa-Geo package in Python (Wang et al., 2022). The GA was implemented using DEAP, an open-source Python library for evolutionary algorithms that supports parallelization (Fortin et al., 2012). With a human-centric focus, the objective of the hybrid ABM-GA model is to minimize overall evacuation time for affected residents. The model was calibrated using data from a real-world student residential community, incorporating its diverse facilities and population characteristics. The following subsections detail the ABM, GA, and calibration settings.

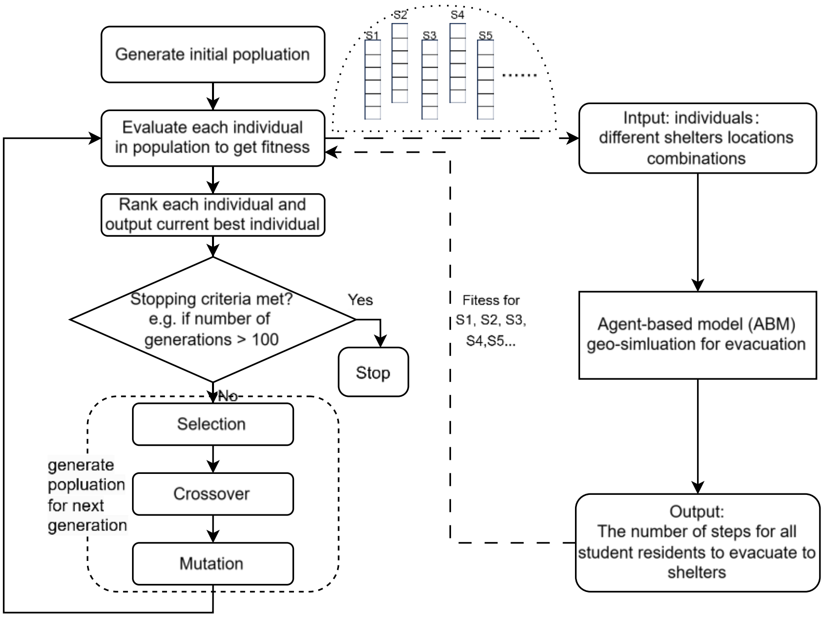

Figure 1: hybrid ABM-GA optimization model

Description of Agent-based Model for Simulating Microscopic Residents' Behavior

Entities, state variables, and scales

The ABM model includes three types of entities: the main model, space, and agents. To fully account for the complexity of evacuation, we have designed five types of agents: *Student Agent*, *Building Agent*, *Stairwell Agent*, *Shelter Agent*, and *Region Agent* which are described in the following:

- *Student Agent* represents a student resident who evacuates from a building and proceeds to a shelter during a disaster. **Table 1** shows the related state variables for student Agents.
- Facilities Agents, including *Building Agents, Stairwell Agents, and Shelter Agents*, can interact with student agents, and the relevant state variables are presented in **Table 2**.
- *Region Agent* is utilized to generate the boundaries of the student community and does not participate in the dynamics of ABM (**Table 2**).

Table 1. State variables for *Student Agent*

Variable name	Variable type	Brief description
evacuate_state	*categorical*	Five types: Focused, not evacuate, building evacuate, stairwell evacuate, neighbor evacuate, in shelter
unique id	*string Unique*	identifier of student agent
student_layer	*integer*	The floor where the student is located
geometry	$\{float, float\}$	position of agent
distance_onestep	*float*	The number of floors the student moves per step
stairwell_onestep	*float*	The distance the student moves per step
stairwell_target	*agent*	The stairwell the student decides to go to
stairwell_network_index	*integer*	The index of the walking network node closest to the agent's stairwell
shelter_target	*agent*	The shelter the student decides to go to
shelter_target_index	*integer*	The index of the shelter in the walking network
short_path	*list*	The indices of the nodes on the shortest path from the stairs to the shelter
Range_find_stairwell	*integer*	The range distance for finding a stairwell
Range_find_shelter	*integer*	The range distance for finding a shelter
Range_be_activated	*integer*	The distance at which one is influenced by others to evacuate

Table 2. State variables for *facilities agents* and *region agent*

Agent type	Variable name	Variable type	Brief description
Building Agent	unique id	*string Unique*	identifier of building agent
	geometry	$(\{float, float\})^n$	position of agent
	evacuate_state	*categorical*	Two types: no student here, student still here
	init_layer_num_student	*integer*	The initial number of students on each floor of the building
Stairwell Agent	unique id	*string Unique*	identifier of stairwell agent
	geometry	$\{float, float\}$	position of agent
	evacuate_state	*categorical*	Two types: stairwell in congestion, stairwell not in congestion
Shelter Agent	unique id	string Unique	identifier of stairwell agent
	geometry	$\{float, float\}$	position of agent
Region Agent	unique id	string Unique	identifier of stairwell agent
	geometry	$(\{float, float\})^n$	position of agent

In the **main model**, various agents are organized in the space and behave according to schedule. The ABM takes the geojson files, depicting the physical built-environment conditions of the study site, as the input to set parameters and create *Building Agent*, *Stairwell Agent*, *Shelter Agent*, and *Region Agent* (**Figure 2**). Data collector functions are used in the model to collect the states of different types of agents, including 1) the number of *student agents* in various evacuation states, 2) the number of *Stairwell Agents* that are or are not in a congested state, and 3) the number of *Building Agents* that have or do not have evacuees at the end of each simulation run.

The **space** entity utilizes and customizes the space module in the mesa-geo package. Space entity is a space with a projected geographic coordinate system of EPSG:3415, which the unit is in meters. This allows us to calculate the actual distances between agents, making the simulation experiments more realistic.

The spatial extent of this model is a student resident community of The Chinese University of Hong Kong, Shenzhen (CUHK-Shenzhen), as indicated by the red rectangle in **Figure 2**. The number of time steps for this model is set to be a total of 50 steps, with each step representing 10 seconds in the real world.

Figure 2. CUHK-Shenzhen campus (ABM development area)

Overview of the Process and Scheduling

After defining the different types of entities and agents, the first step of the experiment is to initialize the different types of agents and their state variables mimicking the real-world setting. Specifically, GEOJSON files containing the boundaries of the student community and the locations and configurations of Stairwells are used to initialize the *Region Agent* and *Stairwell Agents* within the model. The possible geographic locations for shelter sites are obtained from a GEOJSON file. Shelters are initialized based on model input variables, specifically a list of indices representing the potential locations of the shelters. Additionally, a walking network for student agents during outdoor evacuation is instantiated based on a GEOJSON file. **Table 3** presents these input data.

Table 3. Input data for ABM

Names	**Type**	**Brief description**
buildings	*GeoJSON*	GeoJSON shapefiles for student dorms buildings
boundary	*GeoJSON*	GeoJSON shapefiles for community region boundary
stairwell	*GeoJSON*	GeoJSON shapefiles for stairwells
available_shelters	*GeoJSON*	GeoJSON shapefiles for available shelters
walking_network	*GeoJSON*	GeoJSON shapefiles for lines of walking network
shelter_list	*list*	shelter index list e.g., [1,34,89,22,11,10]

As shown in **Figure 3,** *Region Agent*, *Building Agents*, *Stairwell Agents*, and *Shelter Agents* will be instantiated and then placed into the schedule or space in this order, allowing the agents to be activated in a scheduled sequence and interact within the space. The initialization of *Shelter Agents* includes randomness, where students are placed in different buildings and floors, and are assigned varying evacuation speeds: a uniform distribution between 1-1.4 m/s for horizontal movement, and a uniform distribution between 0.8-1.2 floors per 10 seconds for descending stairwells.

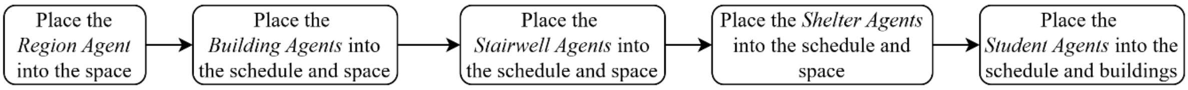

Figure 3. The instantiation process in the model

This model simulates the complete process of student residents evacuating from a building to shelters and demonstrates the step-wise decision-making process of student residents from indoor to outdoor environments. When the “student” is within the residential building, he will go through the process including being activated for evacuation; moving towards stairwells; and moving downward stairs. When the “student” evacuates from the building, he needs to make decisions related to searching for shelters; and then moving to shelters.

During each simulation experiment, the *Student Agent* and *Facility Agents* update their states at each time step according to pre-defined rules (**Figure 4**). In each time step, different agents undergo multiple processing steps and determine their state for the next step. Specifically:

- *Student Agent*: Each student agent is randomly initialized to one of three states: “focused”, “not evacuate” and “building evacuate”. As the evacuation process progresses, this state may transition to “stairwell evacuate”, “neighborhood evacuate”, and “in shelter” based on its location. During each step, the evacuate states of the student agent are first checked. If the evacuation status is “focused” or “not evacuate”, it indicates that the student agent has not started evacuating. If the evacuate state is “focused”, the student agent will begin evacuating if the number of evacuating people within their activation range exceeds a pre-defined threshold, e.g., ten. If the evacuate state is “not evacuate”, the student agent will begin evacuating if at least three people within their activation range are evacuating. If the *student agent* is in the “building evacuate” state, it has a probability of selecting one of the two nearest stairwells and proceeding towards it, depending on the specific context of the scenario. If the student agent arrives at the stairwell, the evacuation state turns to the “stairwell evacuate” state. For student agents in the “stairwell evacuate” state, if the evacuation state of the stairwell they are in is a stairwell in congestion, the student agent's descent speed is reduced to 0.3 times the normal speed. Student agents in the “neighborhood evacuate” state will probabilistically choose one of the two nearest shelters. Then, the student agent will head to the selected shelter through a walking network. Upon reaching the shelter, the student agent's evacuation state transitions to in shelter. **Figure 4** shows the overall decision process of a *Student Agent*.
- *Building Agents*: query the number of *Student Agents* within the building. If there are no evacuating students within the building agent, the evacuation state of the building agent changes to “no student here”; otherwise, it remains “student still here”.
- *Stairwell Agents:* query the number of *Student Agents* within the building. If the number of student agents within the stairwell agent exceeds a pre-defined threshold, e.g., 20, the evacuation state changes to "stairwell in congestion"; otherwise, it remains unchanged.

During each time step, the step function is called. All *Facilities Agents* in the schedule are updated in random sequences, and then *Student Agents* in the schedule are updated in random sequences too. At the end of the simulation experiment, the evacuation state of student agents at each time step and the evacuation situation state of each facility are collected.

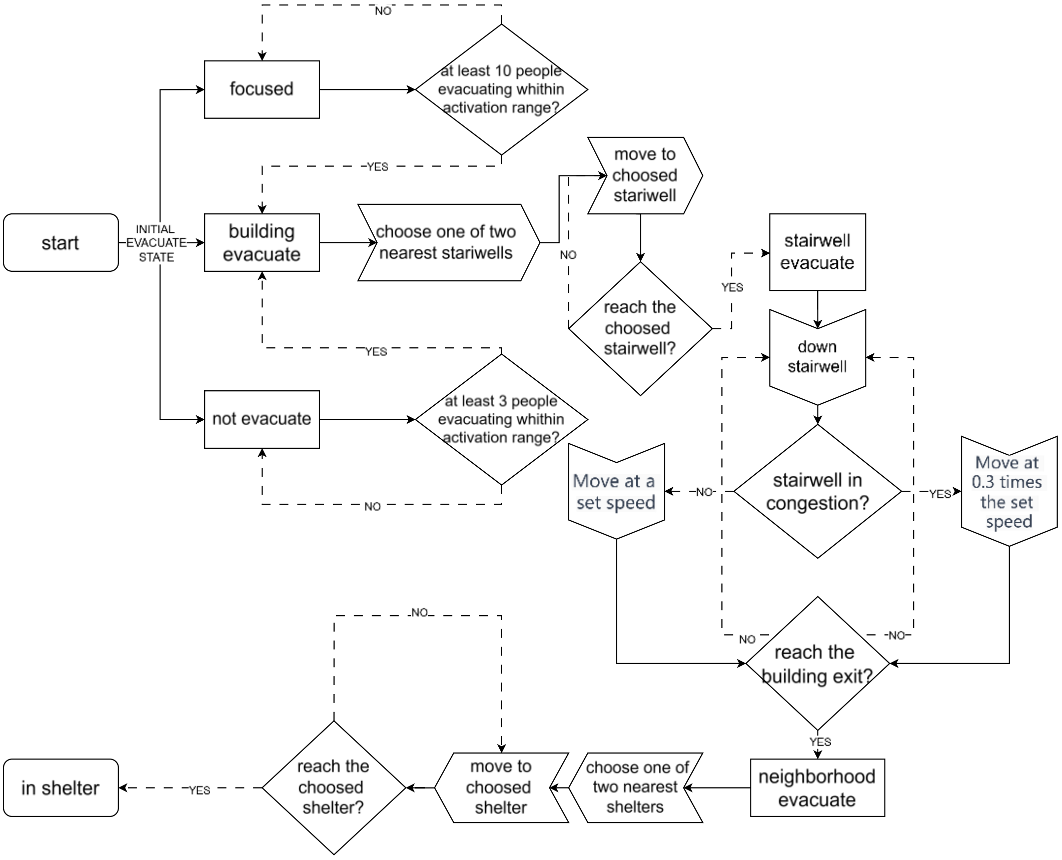

Figure 4. Process Overview for *Student Agents*

Visualization. Figure 5 displays the visualization interface of the simulation experiment. This interface allows users to stop, reset, and run the model and adjust the parameters used in the ABM.

Figure 5. Visualization interface of ABM

Description of Genetic Algorithm for Shelter Site Optimization

In this study, the GA algorithm is used to solve the shelter location allocation problem. GA is an effective and robust optimization tool by simulating the natural evolution and the process of artificial selection and breeding to obtain optimal solutions (Carrese et al., 2021). GA has been applied to the shelter location selection problem in previous studies (Hu et al., 2014). As shown in **Figure 1**, The first step of GA is to generate an initial population of random solutions. Each solution in the population is called a chromosome, which specifies a sequence of values. Each value in the chromosome is considered as a gene. Secondly, the fitness of every solution is evaluated according to the objective function and those solutions are sorted. The third to the fifth steps are used to breed a new population. The third step is to selectively retain the more optimal solutions based on selection rules while also supplementing with random solutions. The fourth step is to conduct crossover, i.e., exchanging some genes between two chromosomes, to generate new chromosomes. In the fifth step, mutation is performed. Mutation has a probability of changing one gene in a chromosome. The crossover and mutation process resemble natural evolution, and hence optimal solutions represented with better chromosomes can be obtained through generations of evolution. The GA loop stops when the stopping criteria are met.

In this study, we construct chromosomes by considering combinations of shelters as chromosomes and encoding each potential shelter location from available shelters as a gene within the chromosome. For the initialization of chromosomes, each shelter is selected with an equal probability. **Figure 6** below illustrates the chromosome representation. **Figure 6(a)** shows all possible shelter locations, while **Figure 6(b)** displays the combination of shelters corresponding to a chromosome. The numbers shown on the chromosome are the shelter IDs, where each ID corresponds to the geographical location of a shelter. With these IDs, GA can update and select chromosomes, while the ABM can retrieve the properties of specific shelters.

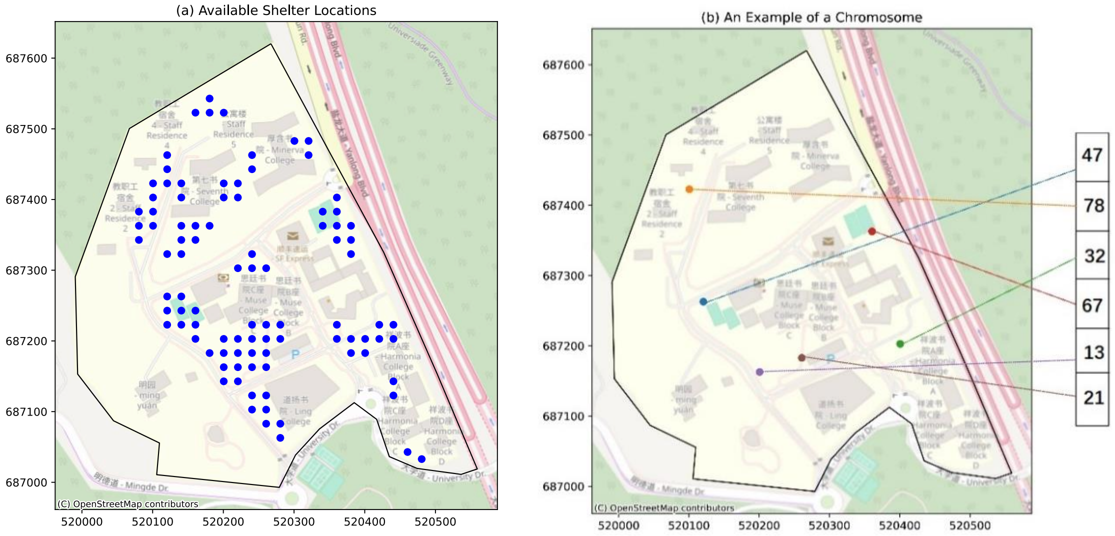

Figure 6. (a) Available Shelter Locations and (b) an Example of a Chromosome

In this study, GA is used to solve the lower-level problem, which means the optimization objective is to minimize certain criteria as much as possible. Specifically, we set the cumulative time for evacuation as the criteria for minimization. In our algorithm, we use the ABM model as the fitness function of GA and the evaluation criterion for solutions. The chromosomes in the GA population will serve as the input for the ABM, and the output of the ABM is the fitness value corresponding to each chromosome (**Figure 1**). Mutation and crossover operations are employed to update each generation. The selection operation improves the average quality of each generation by retaining superior shelter combination chromosomes. This study employs tournament selection, which promotes diversity while selecting more optimal solutions. GA provides 100 shelter location combinations as input variables for the ABM model in each generation. GA stores and outputs the optimal shelter location combination for each generation based on the ABM model output. The parameters for this GA are as follows: a population size of 100, a maximum number of generations of 100, a 30% crossover rate, a 30% probability of mutation, and a tournament size of 3.

SCENARIO EXPERIMENT RESULTS

In emergency evacuations, there often exist various scenarios that can have uncertain impacts on shelter location allocation optimization. The time of nighttime evacuations will directly affect the number of student evacuees who are in deep sleep or other focused states, thereby influencing the contagion of evacuation and decision-making behaviors during the initial stages of the evacuation. Familiarity degree with the community will impact the decision-making process of student evacuees in locating the evacuation facilities. Those scenario variables can be encoded in the ABM parameters (**Table 4**).

Table 4. ABM parameters for variable setting

ABM parameters	**Variable setting**	
Initial ratio for evacuate states of *Student Agents*: [focused: not evacuate: building evacuate]	At 0:00 [5:5:2]	At 3:00 [5:2:1]
Likelihood of selecting the nearest and second-nearest stairwell or shelter (*Student Agents*): [nearest: second-nearest]	Familiar with the community [0.95:0.05]	Not familiar with the community [0.7,0.3]

Based on these variables, we establish three experiment scenarios: 1) At 0:00, Not familiar with the community;

2) At 3:00, Not familiar with the community; 3) At 0:00, Familiar with the community. Optimization results show that each scenario experienced early premature convergence. As shown in **Figure 7**, we selected the 5th, 50th generation, and the final optimization results.

Using Scenario 1—where a disaster occurs at 0:00 AM and only 70% of students are familiar with the community—as the baseline, the simulation results indicate that it takes 470 seconds for all students to reach the shelters when optimized shelter locations are used. However, in Scenario 2, where the disaster occurs at 3:00 AM and a larger proportion of students are in a "focused" state (i.e., asleep), the evacuation time increases by 20 seconds. Additionally, increasing the ratio of students familiar with the evacuation route (i.e., knowing the locations of the nearest evacuation stairwells and shelters) from 70% to 95% reduces the overall evacuation time by 30 seconds, i.e., from 470 seconds to 440 seconds.

These findings highlight the importance of integrating behavioral and contextual data into disaster planning. For instance, emergency managers can analyze residents' activity patterns based on socio-economic distributions and incorporate such factors into the design of evacuation routes and shelter locations. Furthermore, educational campaigns and regular evacuation drills are effective strategies for improving evacuation success rates.

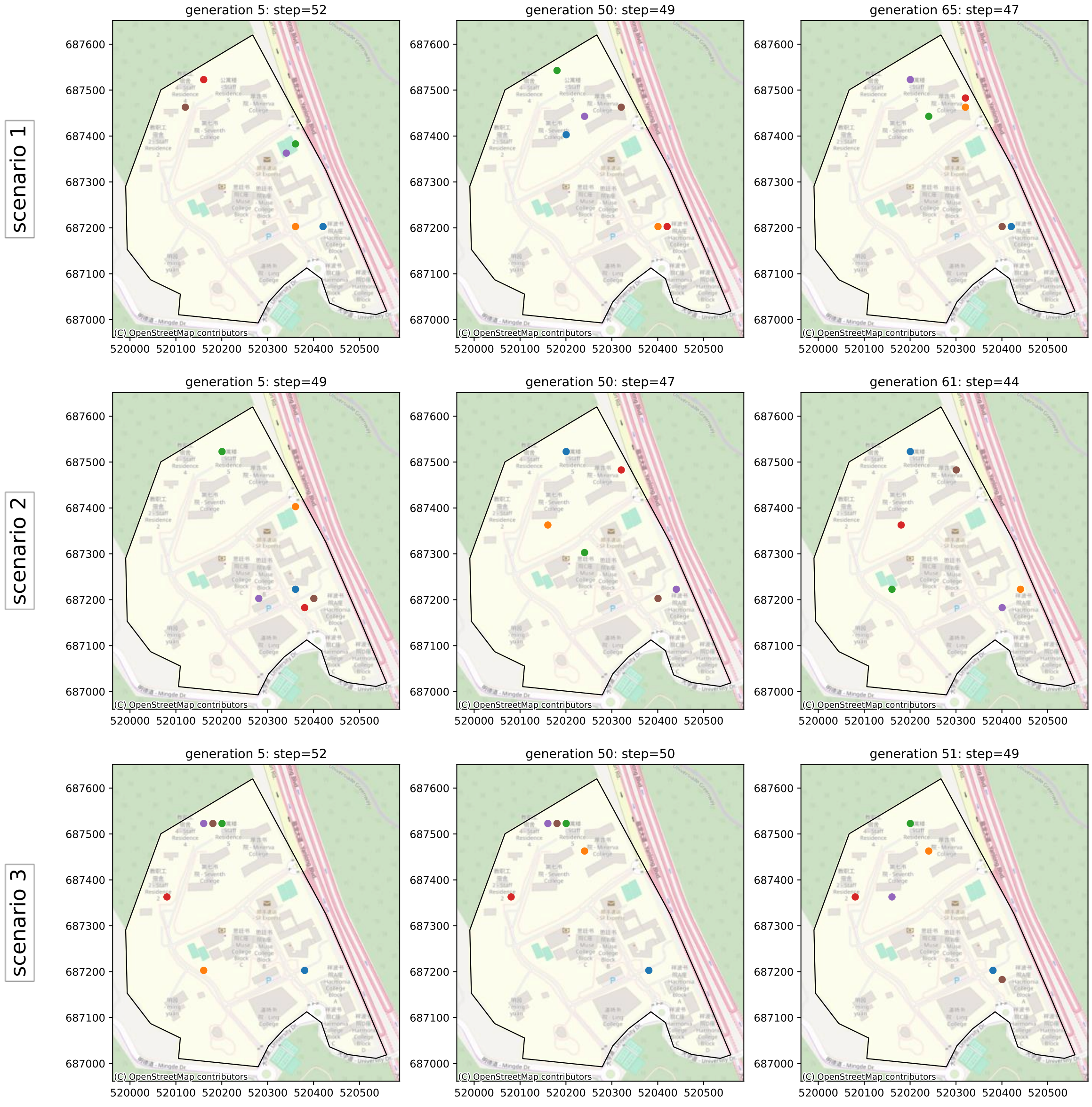

Figure 7: ABM-GA optimization for different scenarios

DISCUSSION AND CONCLUSION

In this study, we developed an approach for shelter location optimization by combining ABM and GA. The output of ABM is used to formulate the fitness evaluation function of the GA algorithm. We applied this method to the student community at the Chinese University of Hong Kong in Shenzhen, China. The results demonstrate that this method is effective in optimizing shelter locations and can flexibly adapt to the scenarios of the community.

Previous shelter location-allocation studies often incorporate both economic (e.g., shelter cost) and non-economic (e.g., evacuation time) constraints using multi-objective optimization methods (Ozbay et al., 2019). However, models based solely on mathematical or GIS techniques often fall short in capturing nuanced human behaviors and human-environment interactions during emergencies. ABM, by contrast, can simulate both the overall evacuation process and individual-level interactions (Nagarajan et al., 2012; Zhao et al., 2015). Therefore, combining ABM with optimal shelter location allocation enables a more detailed and context-sensitive approach tailored to specific communities and populations.

Future work will expand on several fronts. First, we will incorporate existing collision avoidance algorithms and pedestrian movement rules. Second, we aim to construct a social network within the ABM framework, informed by empirical surveys, to better capture behavioral contagion during pre-evacuation and route choice decisions during the evacuation process. For example, evacuees embedded in social networks are more likely to select unfamiliar but proximal shelters. Third, due to the computationally expensive nature of GA optimization with fitness evaluation based on ABM, GPU acceleration can be considered. We plan to explore two CUDA-based strategies in the future work: 1) a hybrid CPU-GPU implementation inspired by Joubert et al. (2022), where agent movement is processed on the CPU while agent states and interactions are managed on the GPU; 2) leveraging the existing GPU-accelerated ABM framework FLAME GPU 2 (Richmond et al., 2023). Fourth, we will further refine the hybrid GA-ABM model in the future by conducting comparative studies to analyze the impact of the ABM component on the convergence of GA. Additionally, we plan to integrate LLM agents into the existing framework, which may further enhance the realism of simulated human decision-making during evacuations.

In summary, this research demonstrates the potential and effectiveness of combining ABM with GA algorithms for optimizing shelter locations within residential communities. Given the evolving nature of urban environments, evacuation behavior is dynamic and context-dependent (Hao et al., 2024), leading to significant variations in evacuation processes and sheltering outcomes. Computer-aided scenario planning, as demonstrated in this study, provides emergency planners with a powerful tool to account for localized conditions and uncertainties, ultimately strengthening community resilience against disasters.

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