Scientific and Social Research, 2026, Volume 8, Issue 4
http://ojs.bbwpublisher.com/index.php/ssr
Online ISSN: 2981-9946
Print ISSN: 2661-4332

When Fire Strikes, Can Buildings Be Swept Faster?

Xipeng Zhao, Xiyu Chen, Xiaoyong Deng

Chengdu Shude High School, Chengdu 610066, China

Abstract: Efficient emergency sweeps in building environments, such as following fires or toxic gas releases, are critical for ensuring occupant safety and structural clearance. Existing search and rescue planning often relies on static assumptions and struggles to account for dynamic interactions among building layout, responder coordination, and evolving environmental hazards, leading to suboptimal deployment strategies. To address this gap, the study proposes a hybrid Cellular Automata-Agent-Based Model for Search and Rescue (CA-ABM-SAR), designated as CAS. The model integrates enhanced cellular automata for environmental representation with an agent-based framework incorporating an action-priority strategy and an improved A* pathfinding algorithm. This hybrid approach systematically accounts for multiple critical factors, including building structure, occupant distribution, responder characteristics, information uncertainty, and time-varying hazards. The study validated the CAS model across diverse scenarios, from single-story offices to complex multi-story hospitals and warehouses. Monte Carlo simulations demonstrate that optimal responder deployment reduces sweep time significantly. Specifically, the study quantified that a reduction of one responder from the optimal number increases sweep time by 17.9%, while light smoke presence across all rooms increases average time by 32.2%. Furthermore, the model was extended to integrate real-time sensor data for dynamic hazard adaptation. The results provide a robust, quantitative framework for emergency planning committees to optimize resource allocation and sweep strategies.

Keywords: Cellular automata; Agent-based model; A* pathfinding algorithm; Emergency sweep; Search and rescue

Online publication: May 25, 2026

1. Introduction

In evaluating the fundamental priorities of human existence, the preservation of life, safety, and security must always occupy the foremost position. Excluding natural disasters, statistical analyses reveal that the majority of human-induced emergencies arise from fire hazards or toxic gas leakages. In such crises, emergency responders serve as the critical agents safeguarding human lives. To enhance survival outcomes, it is imperative to develop an optimized evacuation and search strategy that minimizes rescue time while maximizing operational efficiency (**Figure 1**). A realistic and effective model must extend beyond a single-floor framework, as most contemporary buildings are multi-story structures. In practice, numerous spatial and human factors influence the outcome of emergency responses, including architectural layout, number of floors, positions of staircases and exits, and the heterogeneous distribution of occupants. Moreover, responders frequently operate under severe time constraints and limited situational awareness, necessitating repeated verification sweeps to ensure complete coverage and occupant safety.

Figure 1. Evacuation

1.1. Question restatement

The objective of this project is to develop a series of mathematical models that assist the COMAP in optimizing emergency evacuation sweeps within multi-floor buildings. The overarching goal is to minimize the total clearance time while simultaneously ensuring occupant safety and maximizing the operational efficiency of emergency responders. The modeling process must account for a wide range of critical variables, including but not limited to building layout, the number and proficiency of responders, movement dynamics, verification protocols for completed sweeps, the specific nature of the emergency, and patterns of occupant behavior. The problem specifically requests the following tasks:

Figure out key factors that influence the model, including but not limited to the elements given in the question.

Based on the specific situation, establish a model to simulate the process of these two firefighters efficiently clearing the building during a fire, and calculate the time period for finishing clearance.

Apply the model to additional architectural layouts, then determine inspection order, the optimal number of personnel, their starting positions, and the shortest time to complete the clearance.

Expand the model with more constraints and technical impacts.

Besides, a one-to-two-page summary letter is required for providing practical advice to the Local Emergency Planning Committee, demonstrating the evacuation and clearance strategies and recommendations for feasible strategies.

1.2. Research work

The research work is shown in **Figure 2**.

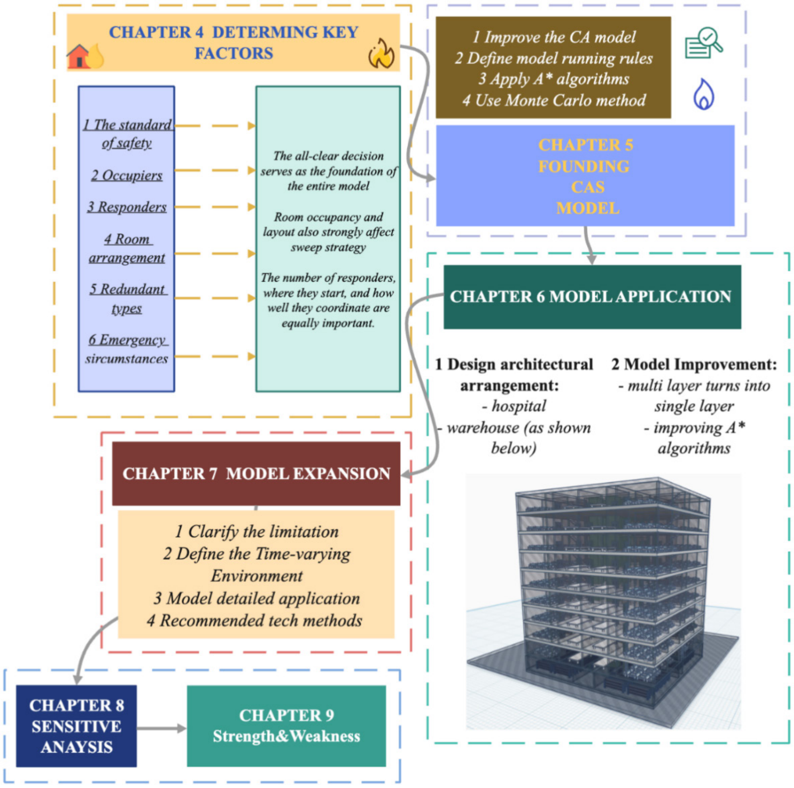


Figure 2. Research work

2. Assumptions and justifications

To simplify the problem, the authors make the following basic assumptions, each of which is properly justified.

Assumption 1: In the floor plan, the authors ignore room types that are few in number and require minimal computing resources (such as restrooms or the principal's office). The authors focus only on the more common and representative room types to simplify the model. In addition, rooms of the same type are assigned a standard size.

Justification: The purpose of the model is to design better search strategies and maximize responder safety, not to perfectly recreate every architectural detail. Simplifying room types allows us to concentrate computing power on the rooms that matter most, which improves overall efficiency.

Assumption 2: Obstacles inside rooms (such as desks, tables, and chairs) are randomly distributed.

Justification: Before an emergency sweep begins, panic can easily disrupt any originally orderly room layout. It is also difficult to find a realistic rule that describes how objects are actually arranged. Using a random distribution helps reflect the chaotic environments responders often face, while also simplifying how the authors model obstacles.

Assumption 3: Space and time can be discretized.

Justification: In reality, time and space change continuously, but running a fully continuous simulation would require far more computational power. To keep the model manageable, the authors simulate everything using discrete units of space and time.

Assumption 4: People of the same category share the same attributes.

Justification: In real life, people's characteristics—such as evacuation speed—vary within a reasonable range. However, these differences are small compared to the main goals of the model. By assigning unified attributes to individuals in the same category, the authors can focus more computing resources on analyzing search strategies and minimizing sweep time, which makes the model more efficient.

3. The development of models

The notations are shown in **Table 1**.

Table 1. Notations

Symbol	Description	Unit
t_{glan}	Time to check the room	s
S_{room}	The area of the room	
k	Room coverage rate	-
O_{room}	Number of occupants in the room	-
t_{cle}	Time to check the non-smoke room	s
t_{smo}	Time to check the light-smoke room	s
x, y	Node coordinates	-
t_{che}	Check time with time redundancy	s

4. Clarifying the key aspects

In emergencies such as fires or toxic gas leaks, evacuating a multi-story building is full of environmental uncertainty, incomplete information, and intense time pressure. A sweep—the core of the emergency response—is not just about walking through every room. Instead, the goal is to confirm as quickly as possible whether anyone is still inside the building as conditions continue to deteriorate, and to move or assist those who remain. Therefore, the key challenge is to build a model that captures the building's structure, responder behavior, the evolution of dangerous conditions, and information constraints. This allows us to quantitatively optimize both sweep routes and overall strategy.

The all-clear decision serves as the foundation of the entire model. In real scenarios, responders face many different situations. If a room is relatively safe, a simple visual check may be enough. But when there is smoke or large obstacles inside, responders must perform more thorough actions—such as a systematic, close-range search—to ensure that no hidden or trapped individuals are missed.

Room occupancy and layout also strongly affect the sweep strategy. Different types of spaces vary in layout complexity, obstacle density, and the number of potential occupants. For example, office areas are usually filled with adults who can evacuate on their own, and they often have high vacancy rates and few obstacles, making sweeps relatively efficient. In contrast, kindergarten classrooms, hospital wards, and chemical labs often contain people who have limited mobility or little emergency experience. These rooms tend to be crowded, high-risk, and require more time to search, and responders may also need to help occupants evacuate.

The number of responders, where they start, and how well they coordinate are equally important.

Working alone keeps the process simple but makes it difficult to handle large, multi-story buildings. A team can finish the sweep much faster, but without good task division and strong communication, they may accidentally search the same area twice or leave certain sections unchecked.

In addition, planned redundancy is an essential part of any sweep strategy. In real disasters, relying on a single pass can lead to dangerous oversights, and as fire or smoke spreads, originally planned routes may no longer be usable. Even though redundancy theoretically increases total sweep time, it provides critical flexibility when conditions suddenly change, and responders need to replan. Therefore, spaces with special functions, high occupancy, or elevated risk levels should incorporate route or time redundancy.

Finally, constraints must reflect the type of emergency. For example, in a smoke-filled fire, the authors need to account for reduced movement speeds, while in a toxic gas leak, responders cannot remain in one area for too long.

Overall, the sweep model the authors aim to build is not a simple path-optimization problem. It is a dynamic system that brings together building structure, occupant distribution, responder characteristics, environmental hazards, and uncertainty in available information.

5. Model 1 CAS

5.1. The basic structure of CAS

Inspired by cellular automata, the model uses sequential and discrete points to represent the spatial configuration of a building [1]. While conventional cellular automata might use an $i \times j$ matrix to represent a physical space of dimensions $a \times b$ (in meters), simulating various states within each grid cell — such as obstacles, responders, occupants, fire conditions, and smoke levels, etc. Therefore, the model adopts an $i \times j \times k$ matrix to represent the space. Here, the $i \times j$ dimensions capture the positional information, while the third dimension, k, is used to represent the various states within each unit of space. A schematic illustration of this mapping is shown in **Figure 3**.

The first two-dimensional matrix represents the layout of a single floor of a building. The authors divide this matrix into two states based on whether the area is within the scope of the search: 0 and non-zero. Areas marked as 0 are not within the scope of this search operation, and responders and occupants will not pass through these areas. Non-zero areas are within the activity range of responders and occupants. Since different areas have different priorities and functional attributes, the authors further categorize them using different numbers. This mainly includes corridors, rooms, and staircases. Different rooms can be represented by different numbers based on their priority.

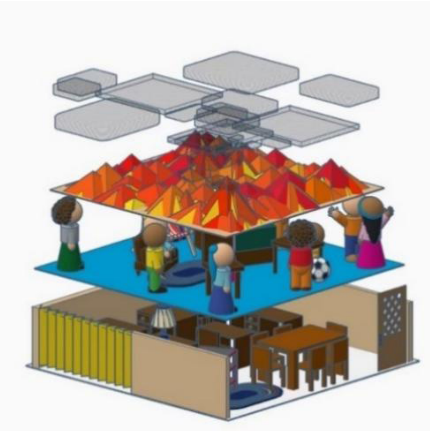


Figure 3. Multi-layer structure

The second two-dimensional matrix represents the distribution of agents (responders and occupants) and obstacles within a single floor of the building. Different groups of agents have their own reasonable attributes and capabilities. Regarding obstacles, the authors have set up obstacles that affect the movement of agents.

The third layer and any additional possible layers represent the variable special environments within a single floor of the building, such as fire, smoke, toxic gases, etc. These often have spatial diffusion effects and can significantly influence the decision-making of agents.

The CAS model establishes a three-dimensional state matrix and determines the capabilities and decision-making systems of agents, as well as the diffusion rules for special environments like fire and smoke. Then, it updates the spatial state at each unit of time to observe the behavior of agents throughout the search and rescue process. Finally, it determines the time required under different search and rescue strategies.

Next, the authors will elaborate on the rules involved in building distribution, agents, obstacles, and special environments.

5.2. Analysis of buildings' arrangement

Firstly, the authors set the unit length of the cell to 1 meter in reality. According to assumption 1, the authors have designed a unified size for each type of room. However, the dimensions of different types of rooms are not the same. **Table 2** provides the different room types and their corresponding attribute information.

Table 2. Different rooms with their attributes

Room Types	Dimensions/ m²	Occupancy Ratio	Vacancy Probability	Occupant Count	Risk Level
Office	10x12	30%	80%	[1,3]	Low
Classrooms (Middle School)	5x6	20%	70%	[1,5]	Medium
Classrooms (Kindergarten)	5x6	20%	60%	[2,8]	High
School Laboratory	8x10	30%	80%	[2,4]	High
Ward	3x4	30%	60%	[1,4]	Medium or High
Warehouse Room (small)	10×11	20%	80%	[1, 3]	Low
Warehouse Room (big)	20×20	20%	70%	[1, 4]	Low

The descriptions for each attribute are as follows:

Room Types: The authors chose office buildings, schools, hospitals, and warehouses as the main types of buildings for the study. Within these structures, the authors identified key room categories, including offices, school classrooms, laboratories, warehouses, and patient wards.

Dimensions: This refers to the actual width and length of each room, measured in meters.

Coverage Rate: This metric measures the extent to which a room is occupied by obstacles. In reality, objects like desks, chairs, and tables are present in the rooms. These tools are considered obstacles during cleaning activities because they will lower the agents' speed and shrink the visibility. In terms of results, a higher coverage rate indicates more obstacles within the room, which in turn increases the amount of time required for responders to complete the cleaning process.

Vacancy Probability: This indicator reflects the probability of whether the room being cleaned by a responder is occupied or not. Not all rooms will have occupants present during cleaning; instead, only a minority of people tend to linger at emergency scenes for various reasons. The authors introduce this probability to quantify that phenomenon. For example, in rooms primarily occupied by healthy adults—such as offices—the vacancy probability is relatively high because such individuals are more capable of evacuating independently, and emergency situations are less common. Conversely, in rooms occupied by minors or individuals with impaired physical functions—such as classrooms and hospital wards—the vacancy probability is lower because these groups lack the capacity for independent evacuation and have less experience or rationality in responding to emergencies. Additionally, spaces like laboratories, which are used less frequently, also tend to have a higher vacancy probability.

Number of Occupants: This attribute indicates the number of occupants present in the room when it is not empty. For this variable, the authors assume that the number of occupants in a room follows a normal distribution within a specified range [a, b]. The detailed formula for this will be explained in the discussion of occupant modeling.

Risk Level: This parameter determines the priority for search and rescue within a room. Rooms primarily occupied by vulnerable groups are assigned higher risk levels, requiring responders to prioritize their search. Other rooms are considered lower priority.

In addition to rooms, the model also incorporates corridor areas connecting rooms and the doors linking them.

For corridor regions, the authors assume that at the start of the cleaning process, these areas are unobstructed and will not typically hinder personnel movement or sight lines under normal conditions, such as in the absence of fire or smoke.

The door plays a crucial role as it is the only passage for people to enter and exit the room. It is located near one end of the corridor and is defined as 1m in length.

Figure 4 is a schematic diagram of the conversion of the building floor plan.

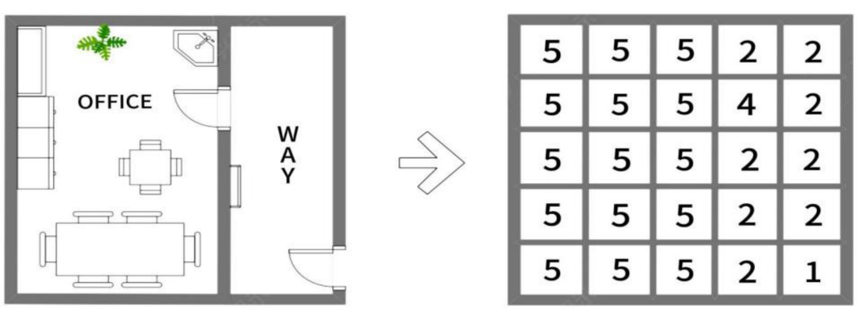


Figure 4. Explanation of the office

In a discrete space, the office area in the figure is represented by 5, where 2 represents the corridor, 1 represents the exit, and 4 represents the doorway. The staircase will be represented by 3, which will be discussed in section 6.2.

5.3. Analysis of agents and obstacles

In the CAS model, the agents are mainly divided into two categories: responders who carry out the cleaning actions and occupants who are the targets of the cleaning process.

Responders are trained personnel responsible for handling emergency situations and performing building cleaning. According to the literature in reference, the average evacuation speed of individuals during simulated evacuations is 1.4 m/s [2]. Since responders are generally more physically fit, the authors assume their normal cleaning speed to be slightly higher, at 1.5 m/s. In certain extreme circumstances—such as in environments filled with thick smoke or flames—their speed would decrease to 0.8 m/s.

Because the unit length of each cell in the model is set to 1 meter and the simulation time step is 1 second, the authors establish that if an agent cannot move a full meter within one time step, their movement will be carried over and completed in the next time step.

When a responder reaches the entrance of a room, they need to spend a certain amount of time observing the room's condition. This observation time can be defined as:

$$t_{glan} = (1+k)\sqrt{S_{room}} \tag{1}$$

where t_{glan} represents the time responders take to browse the rooms, k represents the coverage rate of the rooms, S_{room} represents the size of rooms, ⌈ ⌉ represents ceiling function. When the responder finds the occupant, the responder needs to ensure the occupant's safe arrival at the exit through guidance, carrying, or other means.

Obstacles are items scattered throughout the room that affect agents' movement. According to assumption 2, obstacles are randomly distributed. Generally, a higher coverage rate means more obstacles are present, which increases the likelihood of large obstacles appearing, thus prolonging the time responders need to complete their cleaning tasks.

The occupant is the target that the responder needs to rescue during the cleaning activity. When being rescued, the responder can guide or carry the occupant at the same speed. The model defines the number of occupants within each room. The occupant count follows a normal distribution within the range [a, b], which will be explained further in the context of the modeling.

$$O_{room} \sim N\left(\mu, \sigma^2; a, b\right) \tag{2}$$

where O_{room} represents the number of occupants in the rooms, μ represents the mean of the normal distribution, σ represents the standard deviation of the normal distribution, a represents the minimum value, b represents the maximum value. μ satisfies the following relational expression:

$$\mu = \frac{a+b}{2} \tag{3}$$

To σ, the authors want to ensure that [a, b] covers 95% of the confidence interval (nearly satisfies the 2σ principle), so here is an expression:

$$\sigma \approx \frac{b-a}{4} \tag{4}$$

5.4. Analysis of special circumstances

The CAS model takes into account scenarios in which smoke may be present.

The authors categorize smoke into light and dense types. Light smoke slightly reduces visibility, which increases the time responders need to skim a room. Dense smoke, on the other hand, significantly impacts both agents' speed and visibility, reducing the visible distance to 3 m.

In a light smoke environment, the time a responder requires to skim a room is defined as:

$$t_{smo} = t_{cle} \times (1 + \alpha \cdot C \cdot \sqrt{S_{room}} \tag{5}$$

where t_{cle} represents the time needed to assess the room without smoke, t_{smo} is the time required under light smoke, α is the "smoke time penalty factor" that determines how much the smoke affects inspection efficiency, and C is the smoke coverage ratio, a value between 0 and 1 indicating the proportion of the area obscured by smoke.

In dense smoke conditions, responders cannot determine the room's state from the doorway visually. Instead, they must perform a "carpet search", systematically covering the entire room to ensure that every area is inspected.

5.5. Search and rescue strategy analysis

The authors analyzed the responder's search-and-rescue strategy during the clearing process, which mainly divides into two categories: action-first and information-first.

Under the action-first strategy, the responder enters the building from the exit and goes to the nearest room. They observe from the doorway, and if no one is inside, they move on to the next closest room. If someone is there, the responder escorts that person back to the exit and then continues clearing the remaining rooms until every room is confirmed safe.

Under the information-first strategy, the responder also enters from the exit, but this time they move through the rooms one by one, checking each room and recording where people are located. After every room has been inspected, the responder goes back to the rooms with people inside and brings them to the exit, continuing this process until everyone has been evacuated.

After the analysis and simulation, the authors found that the action-first strategy is superior to the information-first strategy. Because in cases where the number of responders is the same, the information-first strategy will cover more distance from the exit to the occupied room than the action-first strategy, resulting in longer cleaning time. Therefore, unless otherwise specified, the authors will default to using the action-first strategy in the future.

In addition, there is also a redundancy strategy in the search and rescue strategy, namely time redundancy. For high-risk areas, the model increases the time required for responders to stay and inspect the room (t_{che}), simulating a more thorough 'carpet search', even in non-dense smoke environments. The formula is as follows:

$$t_{che} = \beta t_{room} \tag{6}$$

where β represents the redundancy time coefficient in high-risk rooms, with a value greater than 1. represents the time required to check the original room. In the model, β is set to 1.5.

Inspired by a study, the authors use the A*(A-Star) algorithm to handle the path-planning problem between any two points during the clearing process [3]. At each node, the authors calculate:

$$f(n) = g(n) + h(n) \tag{7}$$

where f(n) is the total estimated cost, g(n) represents the cost from the starting point along the path taken so far, which is equal to the distance the responder has already traveled, and h(n) is the estimated cost from the current node to the target. The authors use the Manhattan distance as the heuristic to estimate the distance from a current node to the goal node:

$$h(n) = \left|x_n - x_{goal}\right| + \left|y_n - y_{goal}\right|) \tag{8}$$

where x_n, y_n is the coordinate n of the current node and x_{goal}, y_{goal} is the coordinate of the target node. Overall, the search and rescue strategy of responders is shown in **Figure 5**.

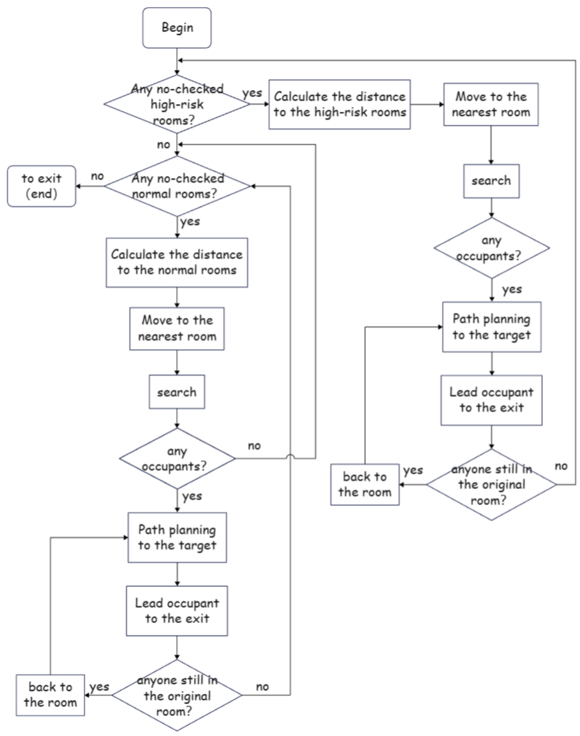


Figure 5. The search and rescue strategy of responders

5.6. Simulation

In Task 2, the authors determine the dimensions of the entire layout, as shown in **Figure 6**.

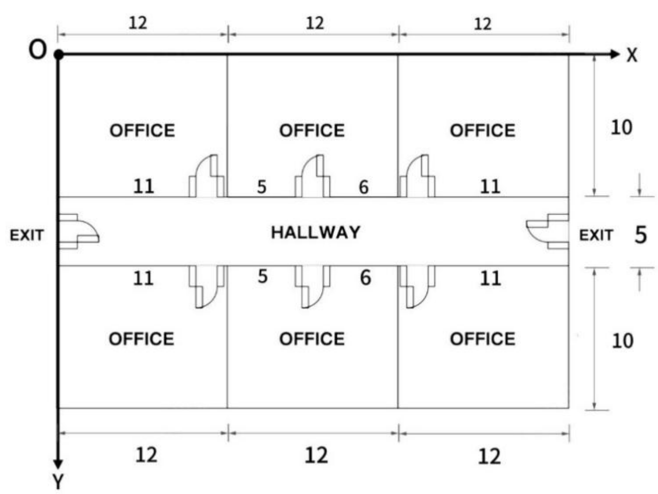
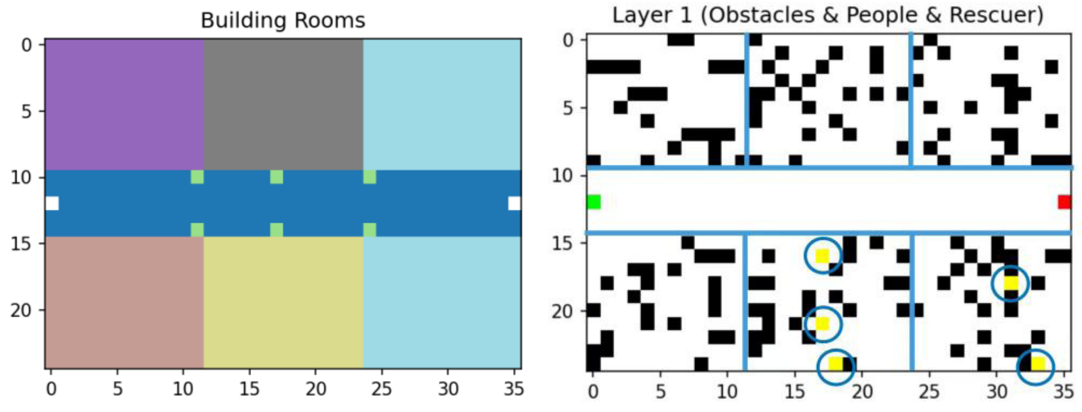


Figure 6. Size of a single-story office room

Applying it to the CAS model can obtain the distribution results shown in **Figure 7**:



(a) (b)

Figure 7. Schematic layout of a single-story office building in the CAS model

Figure 7(a) shows how the single-story office building is represented in the CAS model. The six neatly arranged rectangles stand for the six rooms, the six small green squares in the middle mark the doors connecting each room to the hallway, and the white dots on both sides indicate the building's exits. **Figure 7(b)** shows the layout of obstacles and agents inside the rooms: black areas represent obstacles, yellow marks the occupants, green represents Responder 1, and red represents Responder 2. In this scenario, the two rooms in the lower-right corner contain three and two occupants, respectively, and these are the goals of the rescue.

The authors place one firefighter (responder) at each exit and run the model once to obtain the following results:

At t = 50, the rescue situation is shown in **Figure 8**. At this moment, Responder 1 (green) is inspecting the room in the middle-lower area and has located three occupants. Responder 2 (blue) has already connected with the occupants in the lower-right room—those occupants changed from red (normal state) to blue (linked state)—and is currently guiding them toward the exit.

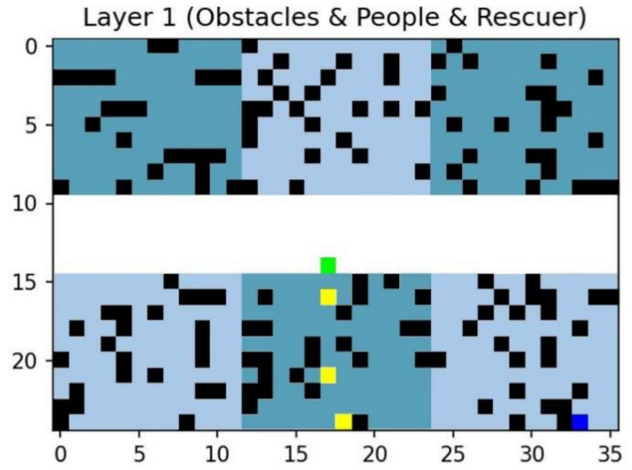


Figure 8. Rescue Status at t = 50

Finally, the model shows that the last occupant is rescued at 105 seconds, and every room has been checked at least once.

Due to the introduction of randomness to simulate uncertainty, including the random distribution of obstacles, occupancy numbers, and room vacancy rates, these settings simulate real-world uncertainty factors through probability distributions and stochastic processes. In order to reduce the errors caused by the randomness of the model algorithm, the authors refer to the Monte Carlo method and obtain stable results through repeated simulations and statistical analysis [4]. Through 100 repeated simulations, the model output a graph of the relationship between sweeping time and frequency (as shown in **Figure 9**), and calculated the shortest and average time consumption. This is one of the core features of Monte Carlo methods, which approximates solving problems or evaluating system performance through a large number of random samples and repeated experiments.

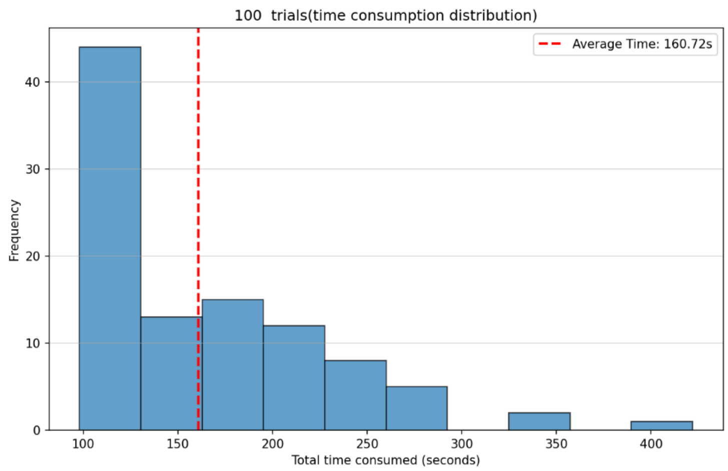


Figure 9. Time–frequency relationship graph for 100 clearing operations

The shortest time required for sweeping activities is 98s, with an average time of 160.72s. Taking into account the potential presence of smoke, the authors compare two scenarios: adding light smoke to two selected rooms and adding light smoke to all rooms. After running 100 simulations for each case, the resulting time–frequency relationship graphs are shown in **Figure 10**:

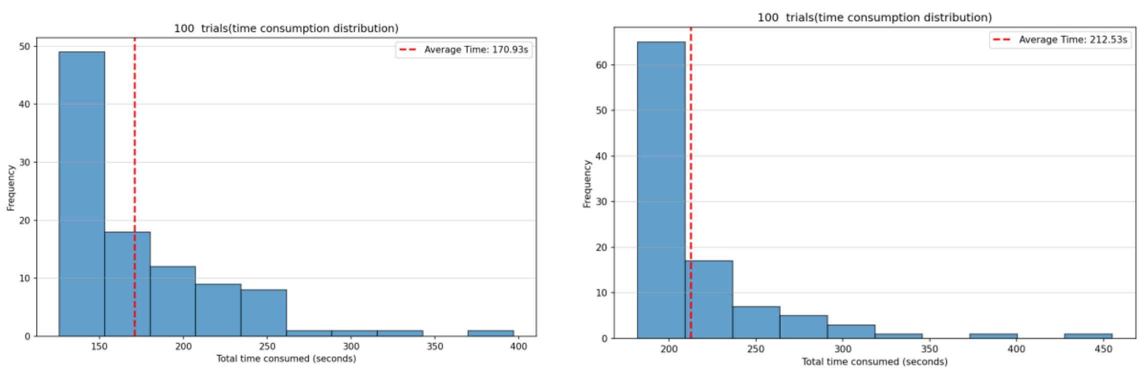


Figure 10. Time–frequency relationship graph for 100 clearing operations with light smoke added to two rooms (Left) and to all rooms (Right)

When adding light smoke to only two rooms, the shortest time is 126s, and the average time is 170.93s.

Compared with the smoke-free situation, the shortest time increased by 28.6%, and the average time increased by 6.4%. For the case where all rooms have light smoke, the shortest time is 182 seconds, an increase of 85.7% compared to smoke-free situations, and the average time is 212.53 seconds, an increase of 32.2%.

6. Model application

6.1. Multi-story building design

According to the real size of the warehouse and hospital, the authors designed the architectural layout of them in **Figures 11** and **12**.

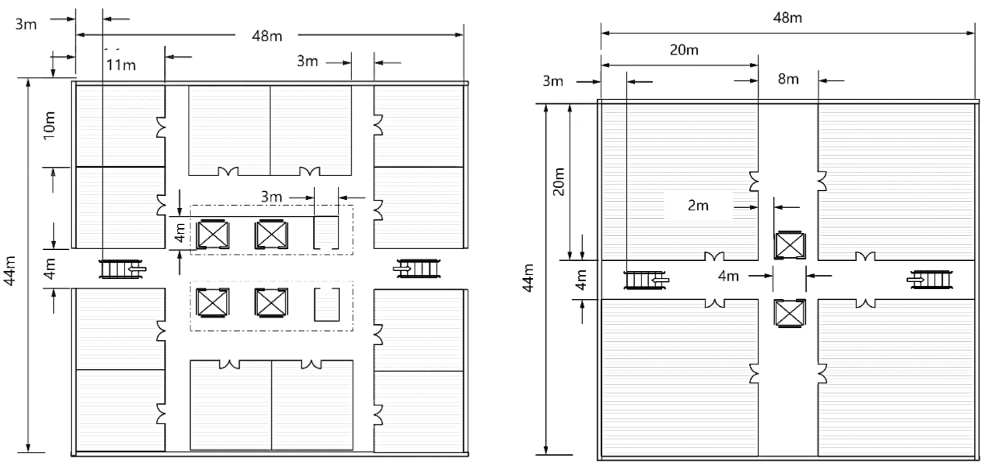


Figure 11. Warehouse floor plan

Figure 11 (left) shows the first-floor layout of a two-story warehouse. Exits are located on both left and right sides, with staircases that can help people go upward and downward. The first floor contains 12 symmetrically arranged small rooms, and there is a central corridor running through the middle. All room doors are positioned along the central corridor. **Figure 11** (right) displays the second-floor layout, where staircases on both sides connect to the first floor. The second floor contains four large, symmetrically arranged rooms, also with a central corridor and doors located along the middle. All dimensions are clearly labeled in the diagrams.

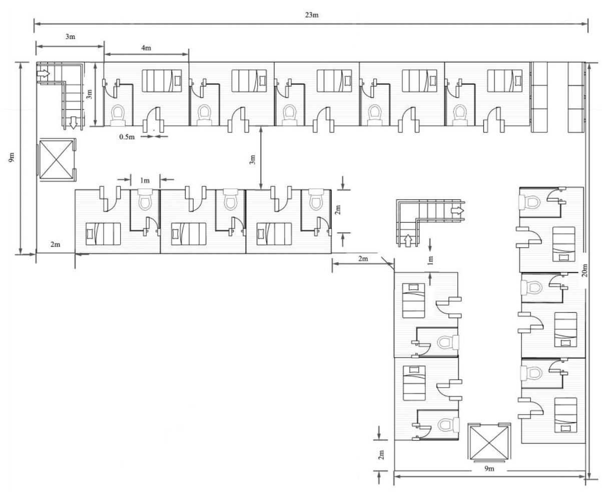


Figure 12. Hospital (inpatient department) floor plan

As shown in **Figure 12**, this two-story hospital (inpatient ward) has exits at the left edge and the bottom edges of this graph, with staircases positioned in the upper-left corner and the central area. Identical patient rooms of irregular arrangement line both sides of the corridors. Since different floors in hospital wards typically have similar layouts, the authors designed both floors with identical distributions. All relevant dimensions are provided in the figure.

6.2. Multi-story building design

In order to solve the simulation problem of agents in multi-layer distribution maps, the authors propose to "piece together" the multi-layer distribution maps, but impose boundary conditions to limit the possible "spatial jumping" problem of agents. That is, setting the cost of agents crossing directly from here to infinity, in order to achieve a more realistic simulation effect.

Specifically, during the CAS modeling process, the authors combine multi-floor layouts along a single dimension before performing cellular automata partitioning, as illustrated in **Figure 13**.

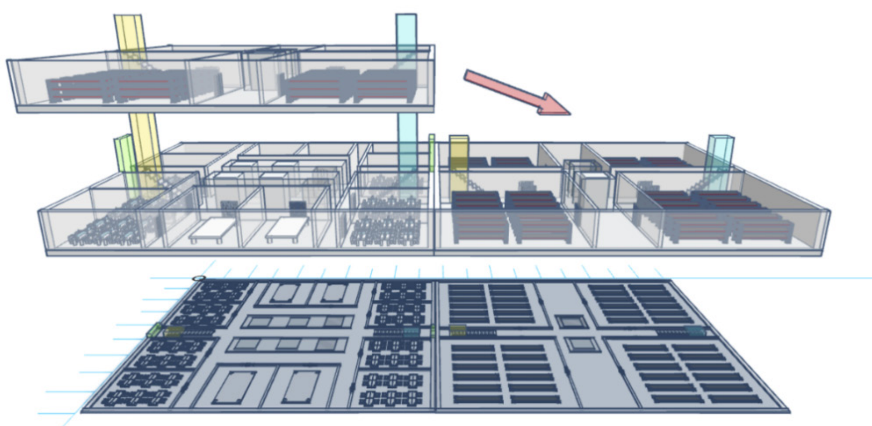


Figure 13. Composite diagram of the multi-floor layout

More closely speaking, when the current node is identified as a stair node, the authors manually add two special types of "neighbor" nodes:

Physical neighbors: the four adjacent cells (up, down, left, right), each with a walking cost of 1 second (s).

Logical neighbors: the corresponding stair cell on the other floor, with a transition cost of seconds (s), which represents the time needed to move up or down the stairs.

After the improvement on the A* algorithm, the update rule for g(n) is:

$$g(n) = min\left[g(n), g(n_0) + w_o\right] \tag{9}$$

where w_0 is the cost defined by the type of neighbor, which means that if n is a normal adjacent cell, then $w_0 = 1$. If n_0 and n form a pair of corresponding stair nodes, then $w_0 = t_{up}$. This setup allows A* to handle many low-cost edges of weight 1 along with a few high-cost stair edges, while still ensuring that it finds the path with the smallest total cost, which indicates the shortest overall time.

Next, the authors will estimate the value of t_{up}. **Figure 14** shows a schematic of the stairs, using a two-flight staircase with a total height of 4 meters as an example.

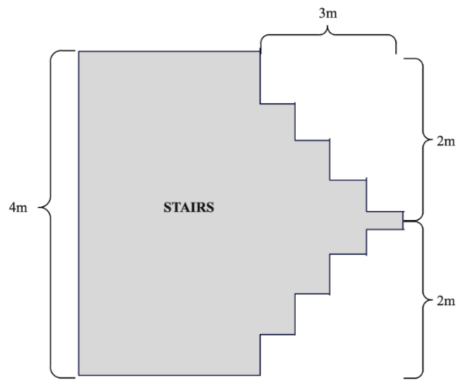


Figure 14. Two-flight staircase

For a single flight of stairs, the horizontal equivalent length is 3 m and the vertical equivalent length is 2 m, giving an overall equivalent length of about 3.6 m. Therefore, the total equivalent length for two flights is 7.2 m. Since the authors assume a 50% speed reduction while climbing stairs, the responder's time to move up one level is: 7.2/(1.5*0.5) s10s. So in the model, the time for responders to climb up and down stairs is defined as 10 seconds.

6.3. Model application

The authors take the data of warehouse into the CAS model, and can get such a distribution in **Figure 15**.

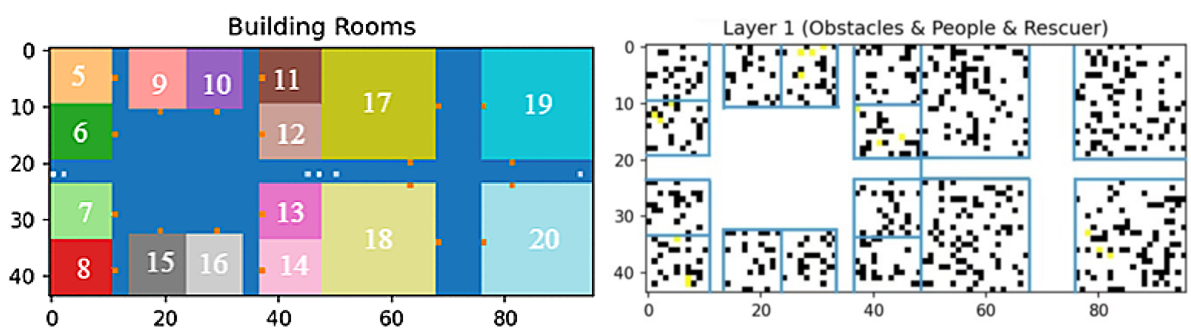


Figure 15. Layout diagram of the two-story warehouse

The left half of **Figure 15** (left) shows the distribution of the first floor of the warehouse, and the markings on the rooms are the room numbers. The larger rectangles distributed along the side are small warehouse rooms, and each room has a door. The white dots indicate exits (near the edges) and staircases (closer to the interior). The right portion displays the second floor layout with four large storage rooms in the corners, each having two doors. The white dots on both sides correspond to the staircases connecting to the first floor. **Figure 15** (right) illustrates potential obstacle configurations and occupant distributions within rooms.

By designing several different plans and running 100 times of CAS simulations for each one, the authors compared how different responders and their starting positions affected the results. The shortest and average times required for each plan to completely clear the building are shown in **Table 3**.

The authors take the data from the hospital into the CAS model to get such a distribution in **Table 3**.

Table 3. Shortest and average times required for each plan to clear the building (units: s)

Number of responders	Number of people and starting position	Min/average time	Time saved
1	1 exit	662/1017.60	
1	1 staircase	658/1037.36	0.6%/-1.9%
2	2 staircase	358/611.85	45.6%/41.0%
2	1 exit + 1 staircase	354/582.72	1.1%/4.8%
2	2 exit	344/605.42	2.8%/-3.9%
3	1 exit + 2 staircase	246/471.93	28.5%/22.0%
3	2 exit + 1 staircase	244/510.79	0.8%/-8.2%
4	2 exit + 2 staircases	204/401.39	16.4%/21.4%

In **Table 3**, "1 exit + 2 staircase" means that one responder starts at an exit and two start at staircases. All exits are located on the first floor, and all staircases are on the second floor. "Time saved" shows the percentage of time reduced compared to the previous plan: a larger value indicates a more significant improvement. From the table, the authors can see that using four responders results in both the shortest minimum time and the shortest average time. The authors also found that as the number of responders increases, the time-saving efficiency changes noticeably, but the rate of improvement gradually decreases. Even so, for the safety of the occupants, the optimal number of responders is still four, starting at two exits on the first floor and two staircases on the second floor. Under this setup, the shortest time needed to fully clear the building is 204 seconds. The sequence in which the responders checked the rooms was recorded as follows:

Responder A: 6–5–7–8–11 *Responder B: 12–10–9–15*

Responder C: 17 *Responder D: 19–20–18–13–16–14*

It can be seen that although the principle of searching for rooms during the inspection process is to find the closest and least searched room, in actual room inspections, there may be a phenomenon of "competing for the nearest room", which is greatly affected by the number and distribution of occupants.

The authors input hospital data into the CAS model to obtain the distribution shown in **Figure 16**.

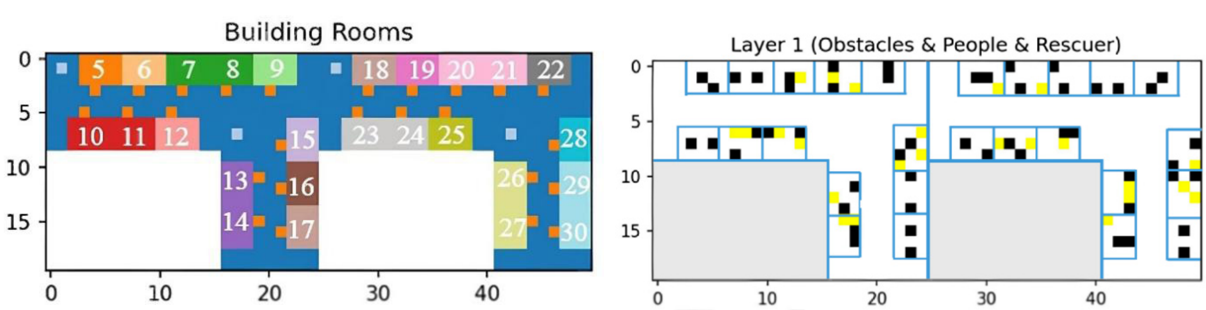


Figure 16. Layout diagram of the two-story hospital

In **Figure 16** (left), the left side shows the layout of the hospital's first floor, and the right side shows the layout of the second floor. The two floors share the same layout, with 13 small rooms arranged along both sides of a hallway. The markings on the rooms are the room numbers. **Figure 15** (right) illustrates the possible distribution of obstacles and occupants inside the rooms.

Using the same approach as before, the authors calculated the shortest and average times required for each plan to fully clear the hospital. The results are shown in **Table 4**.

Table 4. Shortest and average times required for each plan to clear the building (units: s)

Number of responders	Number of people and starting position	Min/average time	Time saved
1	1 staircase	340/599.94	
1	1 exit	328/535.84	3.5%/10.7%
2	2 staircase	204/363.32	37.8%/32.2%
2	1 exit +1 staircase	181/327.94	11.3%/9.7%
2	2 exit	179/324.69	1.1%/1.0%
3	1 exit +2 staircase	126/246.88	29.6%/24.0%
3	2 exit +1 staircase	116/225.63	7.9%/8.6%
4	2 exit+ 2 staircase	96/176.79	17.2%21.6%

Similar to **Table 4**, the overall conclusion remains the same: the optimal number of responders is still four, starting at two exits on the first floor and two staircases on the second floor. In this case, the shortest time required to fully clear the building is 96 seconds. The recorded room-checking sequence is as follows:

Responder A: 10–5–6–11–27 *Responder B: 17–14–13–16–15–25–26–30*

Responder C: 18–23–24–19–20–22 *Responder D: 21–9–8–7–12–28–29*

7. Model extension

7.1. Adding constraints

Based on the information provided in the task, the authors added the following constraints to the model:

Communication between responders has a delay of 5 seconds.

The authors improved movement abilities for the occupants and their awareness of emergencies. When danger occurs nearby, they move away from the hazard until they exit the warning zone.

The authors introduced time-varying hazards, including a fire-spread mechanism and a transition from light smoke to heavy smoke.

The map includes several high-risk areas, and the authors applied a stricter prioritization system to handle them.

The number of responders is lower than the ideal number assumed in the earlier model.

The authors modified the layout to reduce the number of exits and create more dead-end areas, making the environment more irregular and challenging.

7.2. Extended design

First, the authors defined the rules for time-varying hazards. The authors added an additional “fire layer” among the original cellular spaces to model how flames spread through the building. Since the full system is already fairly complex, the authors simplified the fire-spread rules and also added time-varying rules for smoke:

At the start, a randomly generated flame area of size 5×5 appears. The fire then spreads outward at a rate of one cell every 5 seconds. Because fire can only spread when fuel is available, the authors represent this using probabilities: every 5 seconds, if there is an obstacle nearby, the fire spreads with an 80% probability; if not, it spreads with a 50% probability.

Burning flames continuously produce smoke, which spreads faster—expanding one cell every 2 seconds.

A cell burns for 60 seconds before the fire goes out, and once extinguished, it cannot be reignited.

Smoke starts as light smoke, and after accumulating for 120 seconds, it becomes dense smoke.

Walls effectively block both fire and smoke, meaning they can only enter or exit a room through the doorway.

Next, the authors selected the map for the simulation. Using the layout of several real schools as references, the authors designed the two-story school floor plan shown in **Figure 17**.

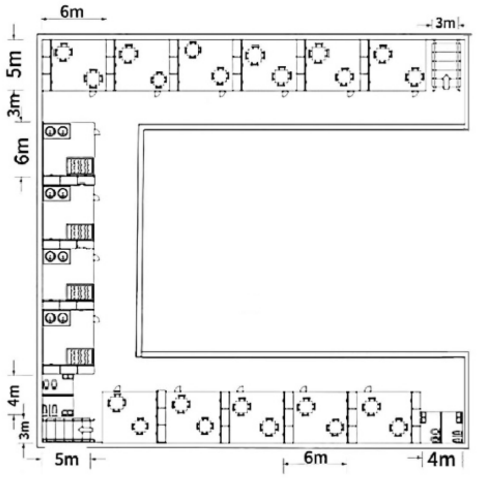


Figure 17. Two-story school floor plan

7.3. Model execution

Inputting the school floor plan data into the CAS model produces a distribution like the one shown in **Figure 18**.

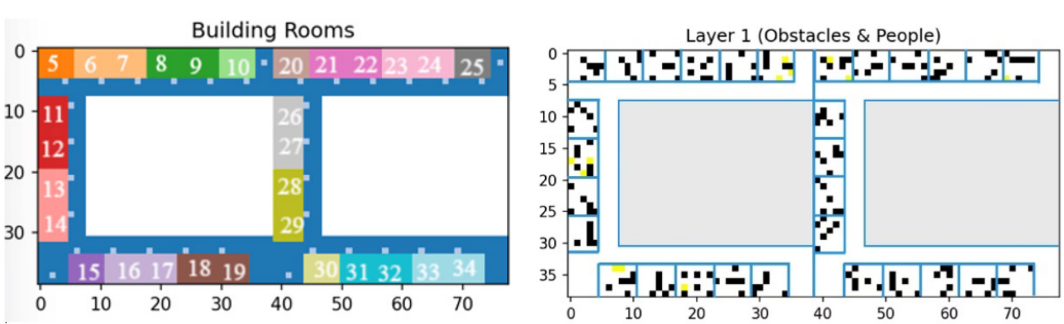


Figure 18. Schematic of the two-story school layout

The authors ran simulations using the optimal plan identified in Task 3, where four responders start sweeping from two entrances on the first floor and the two stairwells on the second floor. Without adding any constraints, the CAS model produced an average sweep time of 551.68s.

When the authors introduced a 5-second communication delay, the average sweep time increased slightly to 566.52s, a difference of only 2.7%. However, when the authors examined individual search paths, they noticed that some areas were being searched multiple times due to the delay, which added about 32.47s to the overall process. Increasing the delay to 30s resulted in an average sweep time of 684.17s, with repeated searches becoming more frequent. This indicates that in real situations, minimizing communication delays between responders is crucial, and if delays cannot be avoided, they should be kept as short as possible.

Next, the authors considered scenarios with fewer responders than the optimal number. Reducing the team to three, two, and one responders produced average sweep times of 650.56s, 880.33s, and 1497.16s, respectively. This represents increases of 17.9%, 59.6%, and 171.4%. The data show that as the number of responders drops below the optimal, the impact on sweep time grows disproportionately, so ensuring an adequate number of responders is a critical factor in real-world applications.

The authors also tested irregular layouts by removing the lower exit on the first floor, creating a dead-end. The average sweep time increased to 717.16s, a 30.0% rise. Further removing the upper stairwell, leaving only a single stair and exit, pushed the average sweep time to 785.01s, a 42.3% increase. This demonstrates that in irregular layouts, responders' average travel distance to exits and stairwells grows significantly. Conversely, a well-organized layout allows responders to reach exits and stairs more quickly, effectively reducing sweep time.

To examine the effect of multiple high-risk areas, the authors designated rooms {11, 12, 13, 14} as kindergarten classrooms and rooms {26, 27, 28, 29} as laboratories. Given the higher potential hazards in laboratories, such as explosions or toxic gas leaks, the authors assigned the highest priority to laboratories, followed by kindergarten classrooms, and then ordinary classrooms. Running the model under these conditions produced an average sweep time of 632.78s, a 14.7% increase. When priority rooms exist, responders head to them first, temporarily overriding the "closest-room-first" rule. Therefore, the more unevenly high-priority rooms are distributed and the farther they are from entrances and stairs, the longer the overall sweep time.

Finally, the authors considered time-varying hazards by adding spreading fire and dynamic smoke. Since flames pose an immediate threat to occupants, the authors adjusted the responders' search strategy to prioritize rooms closer to the fire. **Figure 19** shows the situation in one such simulation.

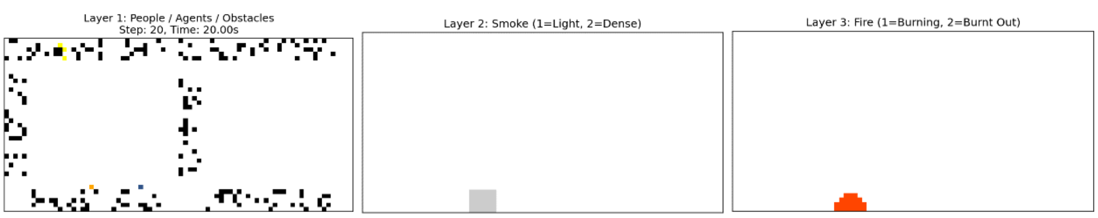


Figure 19. Fire simulation scenario

In this scenario, the fire starts in room 18, which is already filled with light smoke, while responders are prioritizing rooms near the fire. Running the model under these conditions yields an average sweep time of 730.4 seconds, an increase of 32.4%. The most significant change is that responders no longer search the nearest unvisited room; instead, they head toward the room closest to the fire, spending more time traveling. In addition, the dynamic nature of the fire influences their path choices, forcing them to abandon the current "shortest-distance" route in favor of reaching higher-priority areas.

7.4. Technology's impact on the model and proposed recommendation

Sensors and automated building systems—specifically the electronic devices installed throughout a building and the central control systems that manage them—have dramatically changed how the authors approach room-by-room checks during emergencies.

In the CAS model, vacancy probability is a key parameter. The authors usually rely on it to estimate how many people might be in a room and then decide how responders should sweep the building. Once sensors are integrated, the model no longer has to infer occupancy from vacancy rates. Instead, it can pull real-time data that shows exactly whether a room is occupied. At the start of a simulation, any room confirmed to be empty can simply be marked as 0, which helps responders optimize their search path. If a room is empty, they can skip it entirely.

Building automation also changes the rules that govern how fire and smoke spread in the model. Most automated systems include smoke detectors and toxic-gas alarms. In the early stages of a fire or chemical leak, these systems automatically activate sprinklers, remove smoke, and lower fire shutters. The original assumptions were that flames advance one cell every 10 seconds and smoke moves one cell every 2 seconds. But in buildings where smoke control and fire shutters operate effectively, these times can be greatly extended—or fire may not be able to cross into protected zones at all. Even more importantly, responders typically search rooms closer to the fire first, and automated systems can provide an up-to-date, building-wide fire map. That allows responders to constantly adjust their plan and always know where the fire is.

After taking a deeper look into emergency evacuation and search procedures, we've come to appreciate both the severity of disasters and the extreme time pressure responders face. As a result, the authors propose two sets of measures:

All public buildings should install motion and vital-sign sensors. For high-risk buildings mentioned in the paper—such as kindergartens and hospitals—people entering the building should also wear indoor-positioning devices. This would let responders locate individuals directly, not just identify which rooms are occupied.

Buildings should be equipped with smoke alarms and automatic sprinklers to slow down fire spread. Warehouses and laboratories need additional ventilation systems and fire doors to reduce the spread of toxic gases, delay fire movement, and prevent the fire from jumping between different zones.

8. Sensitivity analysis

To understand which parameters the model is most sensitive to, the authors designed multiple sets of input values and ran different simulation experiments. By comparing the differences in their outputs, the authors were able to draw meaningful conclusions.

The data in **Tables 2** and **3**, along with Section 7.3, show that under optimal conditions, the average time needed to clear the two-floor warehouse is 401.39 seconds, the two-floor school requires 551.68 seconds, and the two-floor hospital only requires 176.79 seconds. Since the CAS model responds differently to different types of environments, the authors chose one fixed scenario for the rest of the analysis.

In the warehouse setting, the authors first examined the model's sensitivity to the room vacancy rate. The authors tested four different vacancy rates—60%, 70%, 80%, and 90%—and the corresponding average clearing times were 588.43 seconds, 451.09 seconds, 404.55 seconds, and 288.41 seconds. The relationship is shown in **Figure 20**.

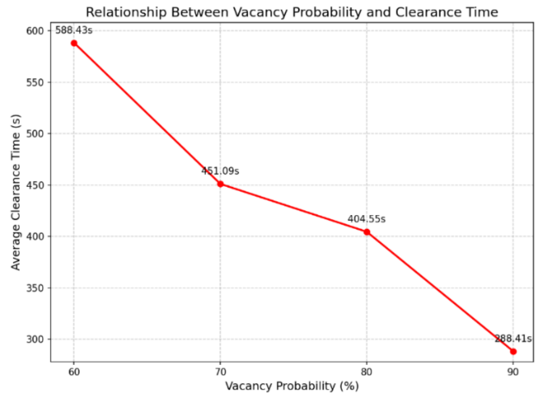


Figure 20. Average clearing time under different vacancy rates

In addition, the authors examined the model's sensitivity to coverage rate. The authors tested four levels—10%, 20%, 30%, and 40%—and, after running the simulations, obtained the relationship shown in **Figure 21**.

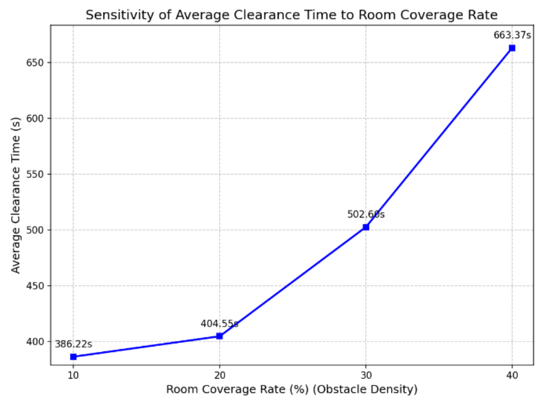


Figure 21. Average clearing time under different coverage rates

Finally, the authors tested different responder speed settings—1.1, 1.3, 1.5, and 1.7 m/s—and obtained the relationship shown in **Figure 22**.

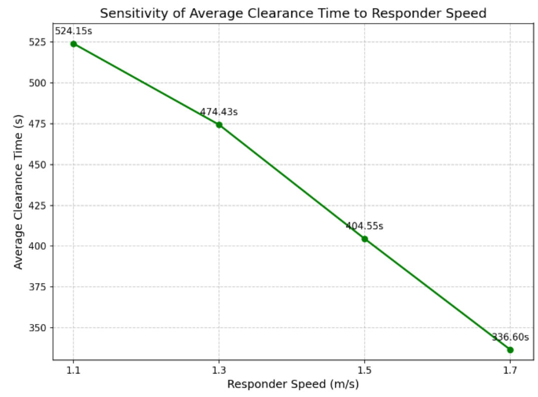


Figure 22. Average clearing time under different speed settings

By calculating the relative changes, the authors found that the vacancy rate produced the largest average variation at 19.4%, the coverage rate followed at 16.6%, and responder speed showed the smallest and most stable change at 13.6%. Therefore, the model is fairly robust with respect to responder speed, but more sensitive to vacancy rate and coverage rate.

9. Strengths and weaknesses

9.1. Strengths

Strong integrative ability and broad applicability. The model accounts for multiple factors at once, including building layout, occupant distribution, responder behavior, environmental risks, and uncertainty in available information. It can simultaneously simulate building structure, human movement, environmental changes, and responder strategies, allowing us to analyze a complex dynamic system in a quantitative way.

High computational efficiency. By making reasonable simplifying assumptions, the authors focused the computing resources on the rooms that matter most, which significantly improved the model's performance.

High flexibility. To better reflect real clearing behavior, the authors introduced some randomness into the process. As a result, the model becomes more adaptable and can handle a wide range of clearing scenarios while maintaining flexibility.

Strong professionalism. The CAS model combines the strengths of cellular automata and agent-based modeling, making its results more reliable.

9.2. Weakness

Sensitivity to key input parameters. The model responds strongly to factors such as room vacancy rate and obstacle coverage. Even small changes in these inputs can produce noticeable differences in clearing time, so the model relies heavily on accurate data.

Simplifications introduced for practicality. To keep the model manageable, the authors ignored room types that are few in number or require minimal computation (such as restrooms or principal offices). In addition, rooms of the same type were assigned a uniform size, which does not fully capture the variation found in real-world buildings.

Disclosure statement

The authors declare no conflict of interest.

References

[1] Hassanpour S, Gonzalez V, Liu J, et al., 2022, A Hybrid Hierarc hical Agent-based Simulation Approach for Buildings Indoor Layout Evaluation Based on the Post-earthquake Evacuation. Advanced Engineering Informatics, 2022(51): 101531.

[2] Kemal BM, Putra H, 2018, An Observation of the Walking Speed of Evacuees during a Simulated Tsunami Evacuation in Padang, Indonesia. IOP Conference Series: Earth and Environmental Science. IOP Publishing, 140(1): 012090.

[3] Hillborg H, Pourlotfi A, 2025, Dynamic Evacuation Route Planning in Complex Buildings.

[4] Tamang N, Sun Y, 2023, Application of the Dynamic Monte Carlo Method to Pedestrian Evacuation Dynamics. Applied Mathematics and Computation, 2023(445): 127876.