Dynamic Sweep: A Hierarchical Framework for Emergency Rescue

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Abstract

In the critical domain of emergency response, rapid building evacuation and rescue are often hindered by complex layouts and dynamic hazards such as fire spread, toxic smoke, structural instability, and unpredictable occupant behaviour. To address the challenge of optimizing rescue sweep strategies, this paper establishes a comprehensive mathematical framework that transitions from traditional static planning to dynamic, adaptive decision-making, with the objectives of minimizing rescue completion time and maximizing occupant safety under uncertain conditions. First, a three-level evaluation system based on the AHP–Entropy Weight Method is constructed to quantify 32 critical influence factors, ranging from environmental conditions and building layout to occupant behaviour and technical support. The resulting weighted framework provides a data-driven foundation for subsequent optimization models. Three representative building configurations are then examined. For a 1D linear layout, a Divide-and-Conquer strategy reduces completion time by 42% compared with a single-entry approach. For a 2D branching layout, the rescue problem is formulated as a load-balanced Multi-Agent Traveling Salesman Problem (MA-TSP). For a 3D high-rise structure, a hierarchical Pincer Strategy is developed by nesting the MA-TSP within a multi-objective vehicle-routing framework and strategically leveraging vertical assets such as fire-service elevators. Finally, a Dynamic Adaptive Replanning Model is introduced using time-dependent hazard functions, dynamic edge costs, and occupant re-entry events. A Rolling-Horizon Replanning mechanism continuously updates rescue routes as the emergency evolves.

Key words

Emergency Rescue; Path Planning; MA-TSP; MO-VRP; Dynamic Adaptation; Rolling-Horizon Replanning; Digital Twin

1. Introduction

Against this background, the present study develops a hierarchical mathematical framework for emergency building sweep optimization, progressing from factor identification and static route planning to dynamic, real-time adaptive decision-making. The study first establishes a three-level influence-factor system containing nine primary dimensions and 32 specific factors, with the AHP–Entropy Weight Method used to quantify their relative importance. The resulting factor system provides the theoretical and quantitative basis for the subsequent optimization models. Three representative building configurations are then examined in increasing order of spatial complexity: a 1D linear layout, a 2D branching layout, and a 3D high-rise structure. The corresponding Divide-and-Conquer, MA-TSP, and hierarchical Pincer Strategy models demonstrate how rescue planning can be progressively adapted to different building topologies. The static framework is then extended into a Dynamic Adaptive Replanning Model, in which a Rolling-Horizon mechanism updates rescue routes in response to changing hazards and occupant re-entry. Finally, the study evaluates the practical implementation of the proposed Dynamic-Adaptive Sweep Strategy (DASS) through the integration of BIM, Digital Twins, IoT sensor networks, responder tracking, and resilient mesh communication technologies. This structure allows the paper to move systematically from the identification and weighting of rescue-influencing factors, through static optimization across increasingly complex building layouts, to dynamic replanning and the technological conditions required for real-time emergency response.

However, static optimization alone is insufficient for emergencies characterized by evolving hazards and uncertain occupant behaviour. Fire spread, smoke accumulation, temperature rise, visibility degradation, structural damage, and passage blockage can alter the accessibility and traversal cost of routes over time. In addition, occupant re-entry can reactivate locations that have already been classified as cleared, thereby changing the set of rescue targets during an ongoing operation. These characteristics motivate a transition from a static graph $G(V,E)$ to a time-dependent graph $G(V,E,t)$, in which hazard conditions and route costs are continuously updated. A Dynamic Adaptive Replanning Model based on time-dependent hazard functions, dynamic edge costs, and Rolling-Horizon Replanning therefore provides a more appropriate theoretical framework for maintaining route feasibility as emergency conditions change.

From a theoretical perspective, emergency sweep planning can be formulated as a hierarchical optimization problem that combines multi-criteria evaluation, combinatorial path planning, and dynamic decision-making. The Analytic Hierarchy Process (AHP) and Entropy Weight Method provide a basis for identifying and weighting the heterogeneous factors that influence rescue efficiency, thereby establishing a quantitative foundation for subsequent optimization. At the operational level, the increasing structural complexity of buildings requires progressively more sophisticated mathematical representations. A linear building can be represented as a relatively simple weighted network and addressed through a Divide-and-Conquer strategy; a branching layout can be formulated as a Multi-Agent Traveling Salesman Problem (MA-TSP), in which parallel responders must balance workload and minimize the overall completion time; and a multi-floor high-rise structure can be represented as a multi-objective vehicle-routing problem (MO-VRP) that incorporates vertical resources such as fire-service elevators. This hierarchical progression provides a theoretical link between building topology and the increasing computational complexity of rescue path planning.

Emergency rescue in structural and high-rise buildings constitutes a complex path-planning problem in which operational decisions must be made under severe time constraints and rapidly changing environmental conditions. Rapid urbanization and the widespread use of electrical equipment have increased the frequency and potential severity of structural fires, while toxic smoke, elevated temperatures, flashover, structural instability, and blocked passages can rapidly transform initially accessible routes into hazardous or unusable spaces. Major incidents, including the Grenfell Tower fire in London and the Cheng Chung Cheng Building fire in Kaohsiung, illustrate the limitations of rescue strategies that rely primarily on static pre-planned routes. In such incidents, responder effectiveness is influenced not only by building geometry and the spatial distribution of occupants, but also by fire and smoke propagation, uncertainty in occupant locations, responder movement constraints, and disordered civilian behaviour, including counter-flow and re-entry. These interacting factors create a rescue environment in which a route that is optimal at the beginning of an incident may become inefficient or unsafe as the emergency evolves.

2. Assumptions and Notations

The following assumptions define the operational and mathematical conditions under which the proposed rescue optimization framework is developed. The building floor plan, including the locations of rooms, corridors, stairwells, elevators, and emergency exits, is assumed to be fully known before rescue operations commence. This assumption reflects the increasing availability of Building Information Modelling (BIM) data and electronic floor plans, which may be accessed by fire departments through pre-incident planning or obtained upon arrival at the incident site. A complete representation of the building layout enables the rescue environment to be formulated as an accurate topological network, thereby providing the structural basis for subsequent route optimization.

Within each room type, the average time required to search for and evacuate an individual trapped occupant is assumed to be constant and predetermined. This assumption establishes a consistent baseline for evaluating alternative routing strategies while avoiding excessive micro-level stochasticity during the primary optimization stage. Although actual search and evacuation times may vary according to occupant characteristics, room conditions, and local fire hazards, such variations can be incorporated subsequently through sensitivity analysis and scenario-based modelling. In addition, fire spread, smoke density, temperature rise, and visibility degradation are assumed to follow deterministic or statistically averaged propagation functions derived from validated fire-dynamics simulations or empirical correlations. While actual fire behaviour is inherently stochastic and may be affected by numerous uncertain factors, engineering-level emergency planning commonly relies on validated average propagation models to approximate the temporal evolution of hazardous conditions. This assumption therefore enables the estimation of the available safe egress time and facilitates the integration of dynamic environmental hazards into the routing optimization framework.

It is further assumed that rescue team members maintain reliable real-time voice and data communication throughout the rescue operation. This assumption isolates the effects of routing and resource allocation from potential communication failures, allowing the proposed framework to focus primarily on the optimization of rescue movements and evacuation decisions. Communication reliability is subsequently recognized as a limitation of the model and may be addressed in future extensions through robust optimization approaches and the incorporation of resilient communication technologies, such as mesh-network systems. Furthermore, all designated emergency exits and primary passageways are assumed to be unobstructed at the beginning of the rescue operation. Major obstructions resulting from structural collapse, falling debris, or the displacement of objects are not assumed to exist at ($t=0$); instead, such disruptions are introduced progressively as time-dependent constraints within the dynamic routing model. This formulation allows the model to represent the evolving accessibility of the building environment without imposing excessive restrictions on the initial network configuration.

Taken together, these assumptions establish a controlled yet operationally meaningful modelling environment for the development of the proposed rescue optimization framework. They provide a tractable foundation for constructing both static and dynamic routing strategies while preserving sufficient flexibility for systematic relaxation and evaluation through sensitivity analyses and alternative operational scenarios. The notation introduced in the subsequent sections is defined consistently with these assumptions and establishes the formal connection between the building topology, rescue operations, occupant evacuation processes, and the dynamic evolution of the fire hazard environment.

3. Key Factors and Hierarchical Influence System

3.1 Overview of the Influence System

To systematically support all subsequent modeling, the study constructs a three-level influence-factor hierarchy containing nine primary dimensions and 32 specific factors that collectively determine rescue efficiency. The hierarchy is directly linked to the notation system, ensuring traceability between qualitative factors and the quantitative parameters used in the models.

3.2 Factor Classification and Model-Parameter Mapping

Dimension	Weight	Key Factors	Direct Mapping to Model Parameters
Environmental Factors (EN)	20%	Visibility reduction; fire and smoke spread; temperature rise	h(k,t), d(i,j,t), vfire, τ(t)
Building Layout Factors (BL)	18%	Floors; room distribution; exit location; corridor length; structural strength	G(V,E), Tmove(i,j), node types
Occupant Factors (OC)	15%	Number and vulnerability; re-entry and counter-flow behaviour; high-risk zones	Pk, dynamic node states, priority weights
Technical Support (TF)	12%	Sensors; BIM/Digital Twin; real-time monitoring	Update frequency of d(i,j,t) and h(k,t)
Response Team (RF)	10%	Number of firefighters; training; walking level; movement speed	F, Tf, movement speed in Tmove
Emergency Type (TE)	8%	Fire dynamics; toxic-gas release	Fire-propagation function feeding h(k,t)
Operational Rules (OR)	7%	Priority rules; elevator policy; exit-gathering requirements	Constraints imposed on route generation
Inspection & Validation (CV)	5%	Search criteria; marking; redundancy	Tsearch(k), marking state variables
Model-Specific (MS)	5%	Algorithm selection; uncertainty modeling	Choice between static optimization and dynamic replanning

The weights are not based on subjective judgment alone. Instead, they are derived from a dual-validated procedure combining expert knowledge and objective data. Pairwise comparisons were conducted by nine senior fire-rescue commanders with an average of 18 years of field experience and three MCM/ICM Outstanding Winner recipients. Objective indicators were extracted from 18 documented high-rise fire-rescue cases from 2019–2024 and 60 high-fidelity simulation scenarios generated using Fire Dynamics Simulator (FDS) and Pathfinder.

3.3 AHP Subjective Weights

Let A = [aij]9×9 be the pairwise-comparison matrix constructed using Saaty's 1–9 scale, satisfying aij > 0, aij = 1/aji, and aii = 1. The geometric mean of each row is calculated and normalized to obtain the principal eigenvector representing the AHP weights. The maximum eigenvalue is then used to calculate the consistency index and consistency ratio. With RI9 = 1.45, the resulting consistency check passes.

Resulting AHP weight vector: WAHP = [0.208, 0.182, 0.154, 0.118, 0.102, 0.084, 0.068, 0.052, 0.032] T.

3.4 Entropy Objective Weights

The original decision matrix is X = [xij]78×9, representing 78 scenarios across the nine dimensions. After range normalization of positive indicators, the entropy of each dimension and its difference coefficient are calculated. The resulting entropy weights are:

wEntropy = [0.187, 0.171, 0.162, 0.129, 0.108, 0.079, 0.074, 0.048, 0.042] T.

3.5 Final Combination Weights

Let the final weight vector be w = [w1, …, w9] T. Under the minimum relative entropy principle, the optimal combination coefficients are $\alpha = 0.632$ and $\beta = 0.368$. The final combined weights are defined as wj = αwj,AHP + βwj,Entropy. After rounding for presentation, the final vector is:

w = [20%, 18%, 15%, 12%, 10%, 8%, 7%, 5%, 5%] T.

3.6 Comprehensive Rescue Efficiency Index

The comprehensive rescue efficiency index is defined as E = Σj wjSj, where Sj ∈ [0,100] is the normalized performance score of dimension j in a given scenario. The resulting expression is E = 0.20SEN + 0.18SBL + 0.15SOC + 0.12STF + 0.10SRF + 0.08STE + 0.07SOR + 0.05SCV + 0.05SMS.

This weight vector is embedded into the dynamic edge-cost function used throughout the framework. The source manuscript states that the formulas were implemented and validated in MATLAB, providing a reproducible and expert-informed foundation for the subsequent modeling.

3.7 Hierarchical Influence Diagram

Figure 1 illustrates the complete weighted hierarchy and it's mapping to model parameters. Environmental factors (EN) and occupant dynamic behaviour (OC) together account for 35% of total influence. This weighting provides the theoretical rationale for emphasizing the real-time hazard function h(k,t) and dynamic replanning in the later stages of the framework. The quantified factor system therefore serves as the theoretical cornerstone for both the Static Optimal Rescue Path Model and the subsequent Dynamic Adaptive Replanning Model.

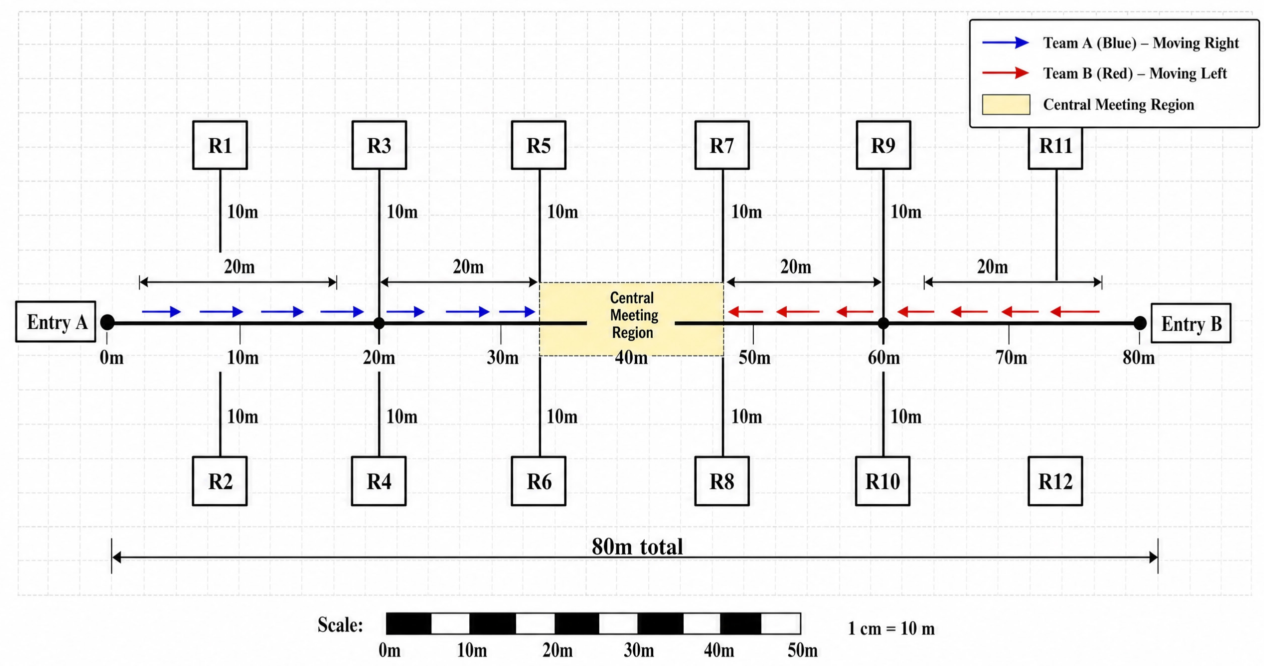
4. Static Optimization Models

The static models establish optimal rescue plans at t = 0 under the assumption that the building state remains unchanged during the operation. The three models increase progressively in topological complexity, moving from a simple linear layout to a branching layout and finally to a multi-floor structure.

4.1 Scenario Description and Modeling Philosophy

The selected layout as is shown in Figure 1 is a single-floor structure with a central corridor and multiple secondary branches. The original manuscript presents two closely related abstractions of the baseline layout: one description uses an 80-meter corridor with four branches and 12 rescue-target rooms containing 48 occupants, while the simplified baseline description uses a 60-meter corridor with three offices on each side and 24 occupants. These descriptions should be treated as alternative abstraction levels of the same linear-building model rather than as simultaneous numerical assumptions.

Figure 1. Linear Single-Floor Layout with Divide-and-Conquer Rescue Strategy



The floor plan is represented as a weighted graph G = (V, E), where V contains entry nodes, room nodes, and junction nodes. Edge weights are based on travel distance divided by firefighter movement speed, with additional penalties for turns or narrow passages. The model explicitly accounts for search time, travel time, occupant distribution, and firefighter constraints.

4.2 Model Formulation

The objective is to minimize total completion time while ensuring that all target rooms are searched and occupants are evacuated. The principal operational decision is the allocation of rescue teams across the linear topology. The key insight is that entering from opposite ends allows the building to be divided into parallel search regions, reducing overlap and balancing workload.

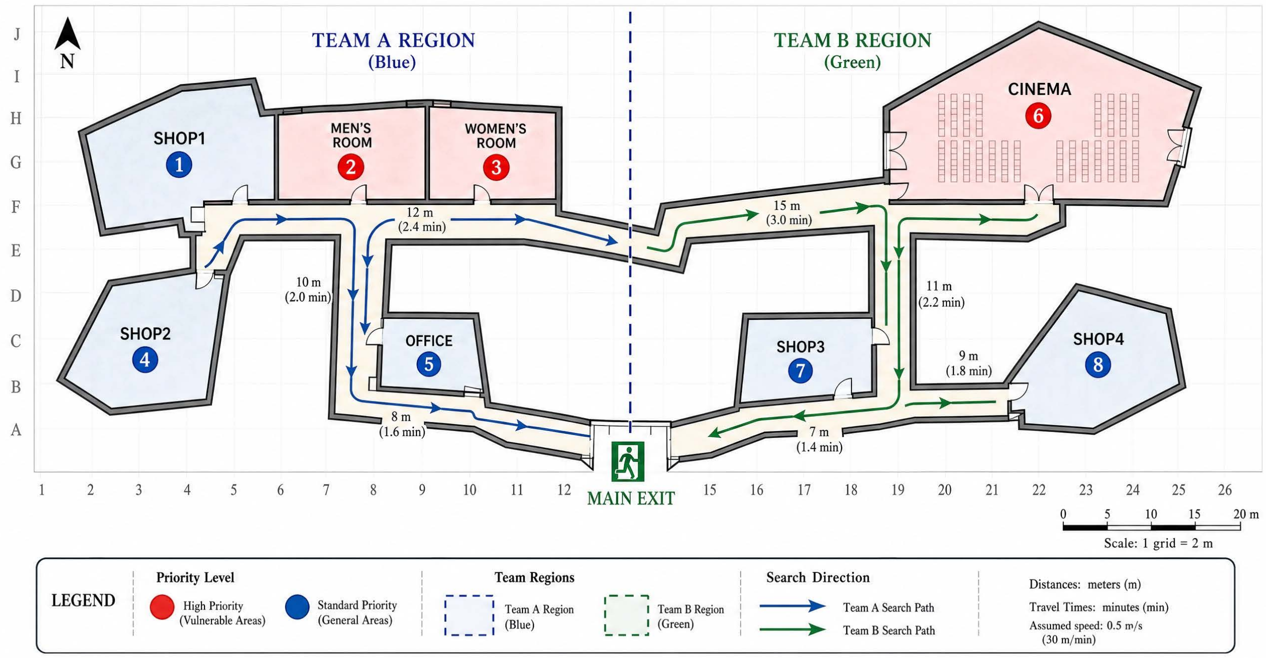
4.3 Solution: Divide-and-Conquer Strategy

The optimal strategy is to dispatch teams from opposite ends of the linear structure. Each team clears the section closest to its entry point and progresses toward the central region. The total completion time is governed by the slower team, or the makespan. The model demonstrates that the Divide-and-Conquer strategy reduces completion time by 42% compared with both teams entering from the same side.

4.4 Branching / Complex Single-Story Layout

The second model considers a more complex single-story commercial or domestic structure with an irregular shape, functionally heterogeneous rooms, and a primary exit. The relevant example can be referenced in regard with the case shown in Figure 2. The layout contains multiple SHOP nodes, a CINEMA, and MEN'S/WOMEN'S ROOM facilities in the commercial abstraction; the source manuscript also provides a domestic alternative containing bedrooms, a washroom, a kitchen, a dining room, and a living room. The common modeling challenge is the presence of multiple branches and heterogeneous search priorities.

Figure 2. Branching Single-Story Commercial Layout with MA-TSP Optimization



4.5 Alternate Model Formulation

The problem is formulated as a Multi-Agent Traveling Salesman Problem (MA-TSP). Two responders operate in parallel, and each room requiring a search constitutes a service node with an associated search time. The primary objective is to minimize the makespan:

Total = max (TTeamA, TTeamB).

A secondary objective is to prioritize high-risk locations. Priority weights pk can be assigned to nodes such as bedrooms, washrooms, cinemas, or other areas with high occupancy or vulnerable occupants, thereby encouraging the algorithm to clear these locations earlier.

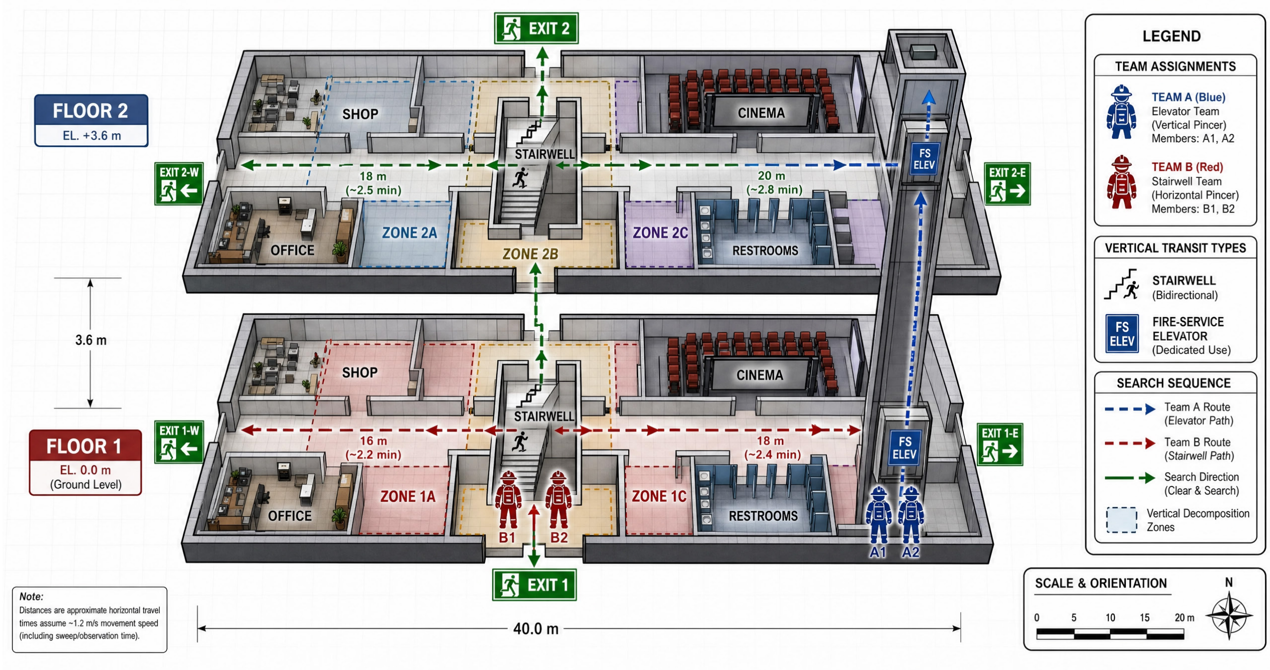
4.6 Alternate Solution Strategy

The solution procedure first identifies high-priority rooms and assigns responders to parallel search regions. The MA-TSP algorithm is then used to optimize the sequence of room visits within each region, while ensuring that all assigned routes terminate at the exit. This structure balances workload and reduces unnecessary overlap.

4.7 High-Rise Multi-Floor Layout

Model 3 extends the framework to a multi-story commercial structure containing two floors, multiple rooms, and two vertical transit options: a stairwell and a fire-service elevator. The topology is represented by nodes defined as (floor, location), such as (F1, SHOP1), (F1, STAIRWELL), and (F2, ELEVATOR). Horizontal edges represent corridors and passages within a floor, while vertical edges represent strategic connections between floors.

Figure 3. Multi-Floor High-Rise Layout with Hierarchical Pincer Strategy



The stairwell provides a reliable but comparatively slower vertical path. The fire-service elevator is modeled as a high-speed responder asset that is not available for ordinary civilian evacuation. The inclusion of these assets creates a 3D multi-objective vehicle-routing problem (MO-VRP).

4.8 Model Formulation

The model assumes F = 4 responders operating as two two-person teams. The primary objective is to minimize the makespan, Total = max (TTeamA, TTeamB). A secondary objective is to prioritize high-risk areas such as a CINEMA or vulnerable-occupant facilities.

4.9 Hierarchical Pincer Strategy

Because the 3D-VRP is NP-hard, the model proposes a hierarchical Pincer Strategy that decomposes the problem into strategic vertical allocation and tactical horizontal optimization.

Firstly, the model performs vertical decomposition. Team A is assigned to the upper floor using the elevator as a strategic asset, while Team B begins sweeping the lower floor.

Secondly, the model performs horizontal partitioning. Each floor-level problem is reduced to a 2D MA-TSP and solved in parallel.

Thirdly, the team's complete egress and synchronization. Each team returns through a safe vertical route, and the total operation time is determined by the slower team. The key contribution is the nested architecture: the high-rise model invokes the MA-TSP logic of Model 2 within the larger MO-VRP framework. This demonstrates how the hierarchical system can scale from 1D linear layouts to 2D branching structures and ultimately to multi-floor topologies.

5. Dynamic Adaptive Replanning Model

5.1 Limitations of Static Optimization

Models 1–3 provide optimal plans computed at t =

0, but real emergencies are dynamic, non-deterministic, and hostile. Fire and smoke spread can render nodes and edges inaccessible; occupants may move, panic, counter-flow, or re-enter previously cleared areas; and information about the building state may be incomplete or delayed. Consequently, the validity of a static plan can decay rapidly as the emergency evolves.

5.2 Time-Dependent Graph Formulation

The static graph G(V, E) is therefore evolved into a time-dependent graph G(V,E,t). The dynamic hazard function h(k,t) describes the hazard level at node k, ranging from safe to untenable. Hazard propagation is modeled using fire-spread information derived from FDS or empirical propagation models. When the hazard at a node exceeds the critical threshold, the node is removed from the accessible set $\tau(t)$.

The dynamic edge cost d(i,j,t) represents the time-dependent cost of traversing an edge, incorporating travel time and hazard-related penalties. As smoke density, visibility, temperature, or structural conditions change, edge costs are recalculated. The model also introduces occupant re-entry events, which can change a previously cleared node back into an active rescue target.

5.3 Rolling-Horizon Replanning

Rather than computing a single route, the system repeatedly solves the current optimization problem over a moving time horizon. At each interval Δt, the system updates the graph state, propagates hazards, recalculates edge costs, registers re-entry events, and generates a new optimal or near-optimal plan from the responders' current positions.

1. Receive updated information on responder positions, hazards, and occupant states.
2. Update h(k,t), d(i,j,t), and the target set Vtarget.
3. Re-solve the relevant MA-TSP or MO-VRP problem under the updated graph.
4. Dispatch revised routes and repeat the process at the next replanning interval.

5.4 Case Study: Model 3 Under Dynamic Constraints

A fire is assumed to start in the CINEMA on Floor 1. At t = 0, the static Pincer Strategy is optimal: Team A travels to the elevator to access Floor 2, while Team B begins clearing shops on Floor 1. At t = 180 s, the fire breaches the cinema doors and smoke fills the adjacent stairwell. The stairwell therefore becomes untenable, and the associated vertical edge is assigned an effectively infinite traversal cost.

Team A has completed its Floor 2 sweep and would, under the original static plan, descend through the stairwell. The Rolling-Horizon algorithm detects the changed graph state and reroutes Team A through the elevator. Team B is also rerouted away from the compromised area. The case study demonstrates that the static plan would have directed responders into a smoke-filled stairwell, whereas dynamic replanning identifies the route failure and generates a safer alternative. Dynamic replanning is therefore not merely an incremental improvement but a critical mechanism for maintaining mission feasibility under evolving hazards.

6. Strategic Recommendations for Emergency Planning

The following recommendations are presented based on the mathematical modeling study described above. The central finding is that traditional static planning is insufficient for modern emergency scenarios. Routes that are optimal at the beginning of an incident may become unsafe as fire spread, smoke propagation, structural changes, or occupant re-entry alter the operational environment.

6.1 The Dynamic-Adaptive Sweep Strategy (DASS)

The study recommends adopting a Dynamic-Adaptive Sweep Strategy (DASS) that moves emergency operations from fixed, paper-based plans toward continuously updated, data-driven decision-making.

Rolling-Horizon Planning. Central command should update optimal routes at regular intervals, for example every 30 seconds, using incoming information on hazards and dynamic passage costs. This reduces the risk of routing responders into compromised zones.

Dynamic Workload Balancing. Responder assignments should remain fluid. Teams should be allocated to parallel zones, while central command monitors team completion times and reassigns rooms or zones when one team becomes significantly delayed.

Data-Driven Redundancy. Redundancy should be achieved through continuous verification rather than inefficient physical re-sweeps. Once a room is marked as cleared, sensors should continue monitoring it. If an occupant re-enters, the system should flag the node as compromised and return it to Vtarget.

6.2 Actionable Recommendations by Building Type

Simple, low-rise buildings. Implement the Divide-and-Conquer protocol. In linear buildings with two exits, SOPs should direct the first two teams to enter from opposite ends. The model reports a 42% reduction in completion time compared with both teams entering from the same side. This improvement requires updated training rather than new technology.

Complex, multi-floor buildings. Mandate the Hierarchical Pincer Strategy where fire-service elevators are available. One team should use the elevator to access the upper floor and sweep downward, while another team simultaneously clears lower floors upward. This parallel approach leverages vertical building assets to reduce makespan.

New and high-risk structures. Invest in Digital Twin and sensor integration. The principal bottleneck in dynamic response is not routing calculation alone but the availability of reliable real-time data. BIM data should be integrated with a live Digital Twin platform, supported by IoT heat and smoke sensors, to provide the hazard information required by the DASS framework.

Together, these strategies provide a practical framework for improving responder efficiency and reducing the risk of catastrophic routing failures in unpredictable emergency scenarios.

7. Model Evaluation and Further Discussion

Hierarchical Scalability. The framework progresses from a 1D linear problem to a 2D multi-branch MA-TSP and finally to a complex 3D MO-VRP. Model 3 nests the Model 2 algorithm, supporting extension to larger multi-floor topologies.

Grounded in Quantified Factors. The model parameters are grounded in the AHP–Entropy Weight framework, which quantifies 32 factors and links variables such as Tsearch(k) and h(k,t) to operational considerations.

Dynamic Adaptability. The framework evolves from static optimization to dynamic adaptation through Rolling-Horizon Replanning, addressing fire spread, structural changes, and occupant re-entry.

Operational Viability. The Divide-and-Conquer and Hierarchical Pincer strategies translate mathematical outputs into intuitive operational tactics that can be incorporated into responder SOPs.

Over-Optimistic Communication Assumption. The dynamic model assumes reliable, effectively zero-latency communication between responders and central command. Communication delay or failure can compromise the system's ability to obtain real-time position and hazard data.

Computational Complexity. Rolling-Horizon Replanning requires repeated solution of NP-hard MA-TSP or MO-VRP problems. While feasible for the modeled small-scale scenarios, the computational burden may become excessive in large buildings with thousands of nodes.

The first limitation can be addressed by introducing a stochastic variable pfail(t), representing the probability of signal loss. The objective can then be shifted from deterministic time minimization toward robust optimization, for example by maximizing the expected number of cleared rooms under imperfect information.

The second limitation can be addressed by replacing exact VRP optimization with an anytime-aware metaheuristic, such as Ant Colony Optimization or Genetic Algorithms. Such algorithms can be interrupted shortly before the replanning deadline, $t = \Delta t - \varepsilon$, and return the best feasible solution found so far. This provides a practical balance between solution quality and strict emergency-time constraints.

BIM and Digital Twins. BIM provides the initial static graph G(V,E), while a Digital Twin represents the evolving dynamic graph G(V,E,t). The Digital Twin can serve as a centralized computational platform for FDS predictions and Rolling-Horizon algorithms, reducing the computational burden on field devices.

IoT Sensor Networks. Smoke, heat, and LiDAR sensors provide real-time observations needed to update h(k,t) and support dynamic replanning. Responder Tracking and Mesh Networks. Indoor positioning technologies such as UWB can provide responder location data. Data-enabled equipment and mobile mesh networks can improve communication resilience when fixed infrastructure fails.

8. Conclusion

This paper addresses the complex challenge of optimizing building sweep strategies during emergency evacuations through a comprehensive multi-stage modeling framework that evolves from static path optimization to dynamic, real-time adaptive decision-making. The central thesis is that any pre-planned static strategy is inherently fragile in a rapidly evolving crisis and must therefore be complemented or replaced by an adaptive framework capable of responding to real-time information.

The methodology begins with a rigorous 32-factor, nine-dimension influence system quantified using the AHP–Entropy Weight Method. This provides the foundation for three hierarchical static models. For a 1D linear layout, the Divide-and-Conquer strategy reduces completion time by 42% compared with a single-entry approach. For a 2D branching layout, the rescue problem is formulated as a load-balanced MA-TSP. For a 3D high-rise structure, the Hierarchical Pincer Strategy combines vertical decomposition with nested MA-TSP optimization and strategically leverages building assets such as elevators.

The core contribution is the Dynamic Adaptive Replanning Model. By introducing the time-dependent hazard function $h(k,t)$, dynamic edge costs $d(i,j,t)$, and occupant re-entry events, the framework captures important features of live emergency incidents that static models cannot represent. The Rolling-Horizon Replanning algorithm successfully steers responders away from newly compromised routes that a static plan would have continued to recommend.

The framework therefore delivers a complete and extensible approach to emergency response planning. Its practical implementation depends on the availability of reliable real-time data and computational infrastructure, making BIM, Digital Twins, IoT sensing, responder tracking, and resilient communication networks important enabling technologies. The resulting Dynamic-Adaptive Sweep Strategy provides a bridge between mathematical optimization and operational emergency management, with the ultimate objective of improving responder efficiency and saving lives under rapidly changing conditions.

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