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Urban swarms: Swarm intelligence for emergency evacuation planning

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ABSTRACT

The relevance of this research is determined by the fact that in the conditions of modern urbanization, the safety of large public facilities increasingly depends on the ability of management systems to quickly and evenly distribute human flows during emergencies. Standard algorithms are focused on thel shortest paths and tend to neglect exit throughput capacity, causing congestion, which in turn critically increases evacuation time. The object of research is the process of emergency evacuation in large-scale, multi-exit buildings, modeled as a capacity-constrained network flow problem. **The aim of the article** is to develop and validate a swarm intelligence model that allows for the effective distribution of human flows between the exits, while taking into account their throughput capacity and reducing the total evacuation time. To achieve this goal, the following **tasks** were solved: a nonlinear objective function was constructed with penalties for congestion; the parameters of swarm algorithms were adapted for searching in congested networks; an empirical assessment of evacuation scenarios was carried out and a compromise between computational speed and stability of solutions was determined. The following **methods** were used in the work: graph theory methods to describe the structure of buildings; mathematical programming apparatus to construct a nonlinear objective function; and swarm intelligence methods to search for the global optimum in a multidimensional solution space. **The scientific novelty** lies in the proposal of a novel objective function that includes strong nonlinear, quadratic penalties for overloading and exit capacities violations. To effectively optimize this high-penalty environment, the basic parameters of the standard particle swarm optimization and ant colony optimization algorithms were changed, resulting in the Modified Particle Swarm Optimization and Enhanced Ant Colony Optimization variants. **The simulation results** for different types of buildings confirmed that the proposed approaches reduce cumulative evacuation delays by up to fifty-five percent compared to classical methods of finding the shortest path. **The practical significance** of the results lies in supplementing existing engineering methods for evacuation planning – which are based on the shortest-path principle – with a load-balancing mechanism that accounts for exit capacities. This eliminates the issues of localized congestion and the overloading of specific exits during crowd evacuations, while also providing an algorithmic foundation for integrating the developed models into BIM systems to enable the automatic generation of safe routes in real time. **Conclusions**. The analysis demonstrates that the proposed swarm intelligence model effectively distributes crowd flows among exits, taking their throughput capacities into account, and significantly reduces cumulative evacuation delays compared to the baseline shortest-path method; this confirms the validity of the developed approach for practical evacuation planning.

Keywords: emergency evacuation; swarm intelligence; capacity constraints; crowd dynamics; path optimization; building safety; human flows; particle swarm optimization; ant colony algorithm; load balancing; mathematical modeling

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INTRODUCTION

Evacuation in cases of emergencies is one of the most challenging tasks in the sphere of urban infrastructure management. In the modern world construction of supertall buildings increases by the day, which leads to significant concentration of people at one place. In case of catastrophe or natural disaster, such structures can become a center of huge casualties and economic losses. In such conditions, even the slightest delay in movement, caused by, for example, blocked exit, can quickly escalate into a very dangerous and life-threatening situation. Systematic reviews on large-scale evacuation planning confirm that failure to account for capacity constraints leads to severe congestion and underestimated evacuation times, which can result in catastrophic outcomes. Therefore, the development

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of reliable automated strategies to manage the flow of people during evacuation is not optional but absolutely necessary to ensure public safety [1].

The scale of this challenge is difficult to overstate. According to the United Nations Office for Disaster Risk Reduction, between 2000 and 2019 over 7,000 major disaster events were recorded worldwide, affecting more than 4 billion people and causing approximately $2.97 trillion in economic losses [2]. Urban environments, with their dense populations and complex infrastructure, are disproportionately exposed to these risks. A single delayed or poorly executed evacuation can transform a manageable emergency into a mass-casualty event – as tragically demonstrated by the 2003 Station nightclub fire in Rhode Island, where 100 people perished within minutes largely due to a single congested exit, or the 2013 Dhaka garment factory collapse in Bangladesh, where inadequate evacuation planning contributed to over 1100 deaths.

In emergency management, efficient evacuation planning is critical for minimizing casualties and reducing economic losses during natural disasters, fires, terrorist attacks, and structural failures. Effective evacuation strategies must balance multiple competing objectives: minimizing evacuation time, ensuring equitable access to exits, preventing crowd congestion, and adapting to dynamic environmental hazards.

Beyond physical infrastructure, human behavioral factors introduce an additional layer of complexity. Under stress, evacuees tend to follow familiar routes, imitate others, and exhibit herding behavior – all of which can amplify congestion rather than relieve it [3]. These psychological dynamics are well-documented in crowd science and must be accounted for in any realistic evacuation model. Furthermore, evacuation scenarios are rarely static: fires spread, structural damage progresses, and hazard zones shift in real time, demanding systems capable of continuous adaptation rather than one-time route assignment.

Traditionally, evacuation has been performed using static signage and the shortest path principle where people simply move to the nearest exit. However, this approach does not take into account realistic limitations of buildings and dynamic crowd behavior. In situations with huge amount of people, the nearest exit often becomes overloaded, whereas the other ones remain underutilized. This phenomenon, also known as “exit saturation”, proves that focusing solely on distance is insufficient in complex environments. Recent studies on pedestrian evacuation under flood conditions demonstrate that single-exit scenarios can increase evacuation time by 30-40 – compared to multi-exit configurations with distributed load [4].

Historical disasters such as the 2017 Grenfell Tower fire in London and the 2022 Mumbai building collapse highlight how inadequate evacuation routing and poor crowd management directly contribute to mass casualties, underscoring the critical need for intelligent, adaptive evacuation systems that can dynamically reroute occupants in real-time.

The main complexity lies in fair people distribution across all the available exits while taking into account their throughput capacity. In the proposed study, evacuation as capacity-constrained optimization problem. Unlike previous approaches, where the throughput capacity of corridors and exits is often assumed to be unlimited, this research allows for the architectural constraints, such as limited throughput capacity and uneven distribution of population. This is especially noticeable in scenarios with extreme overload, where exit utilization significantly exceeds acceptable levels, which in return creates severe pressure on exit infrastructure.

We tackled this problem by leveraging Swarm Intelligence (SI). In particular, Modified Particle Swarm Optimization and Enhanced Ant Colony Optimization were used. These approaches are well suited for complex problems, where it is necessary to find the optimal solution among a large number of possible options. The research suggests using a novel objective function that utilizes non-linear quadratic penalties for congestion, for solving these kinds of challenges. This approach allows avoiding situations where certain routes become extremely overcrowded. Through a comparative analysis across high-rise, shopping mall, and hospital topologies, this paper provides a strong foundation for developing smart, capacity-aware evacuation systems.

Unlike centralized control systems that require extensive infrastructure and single points of failure, swarm-based approaches are inherently robust, scalable, and fault-tolerant, making them particularly suitable for emergency scenarios where communication networks may be partially disrupted or overwhelmed.

This study bridges the gap between theoretical swarm algorithms and practical urban evacuation planning by integrating architectural data, capacity constraints, and dynamic crowd behavior into a unified optimization framework, thereby advancing

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both the scientific understanding and engineering implementation of intelligent evacuation systems.

RELATED WORKS

In recent years, Swarm Intelligence (SI) has been used in crowd management as an effective alternative to traditional static pathfinding methods. A survey paper published in Swarm and Evolutionary Computation offers a comprehensive review of SI techniques such as Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), highlighting their ability to solve non-linear routing problems better than classical algorithms such as Dijkstra or A* [5]. However, the survey also points out a major drawback in existing research: while many studies focus on general route optimization, comparatively few address the mathematical complexity introduced by hard capacity constraints in multi-exit building architectures.

Recent literature has also indicated that neglecting exit and roadway capacity leads to severe congestion and queuing effects in evacuation planning. For instance, hybrid control path planning frameworks integrate dynamic traffic equilibrium assignment to manage real-time network loads. By guiding traffic differently, these frameworks can reduce congestion in emergencies and demonstrate why congestion-aware path planning is more effective than simply following the shortest routes [6].

Moreover, systematic reviews on evacuation methodologies highlight that dynamic traffic assignment and other similar techniques are necessary to account for congestion and behavioral dynamics in large-scale evacuations. These studies find that static routing commonly neglects flow propagation and capacity constraints thus underestimating evacuation times and yielding unrealistic traffic patterns [7].

These findings highlight the value of non-linear, congestion-aware functions, as used in the capacity-aware swarm intelligence models developed in this study.

Despite the significant progress in the field, standard swarm intelligence algorithms still suffer from the same drawback – they too often get “stuck” on the local minima too. The reason for that is mostly the same – infrastructure bottlenecks that cause the search to simply stop before reaching the globally optimal solution. That is why modern researchers are increasingly leaning towards parameter-tuned and hybrid approaches.

One example is Improved Ant Colony Optimization (IACO), where heuristic coefficients are changed dynamically so that agents do not cluster on routes that are locally optimal but actually globally congested [8]. In high-density environments, this is exceptionally important: failing to consider node capacity threshold can lead to not optimized networks with severe overcrowding [9]. Therefore, the objective function in such algorithms is no longer following the “shortest path” principle, it accounts for the network load in general.

Similar logic is also present in modern adaptations of particle swarm algorithm. In particular, the study by Arora et al. recommends the implementation of a dynamic inertia weight control mechanism based on current population fitness metrics (DIW-PSO). This approach provides a flexible balance between global exploration of the solution space and local search (exploitation), which allows the algorithm to adapt to changing conditions and avoid premature convergence in complex multidimensional environments [10].

Zhao et al. (2020) conducted a detailed experimental comparison of several swarm intelligence algorithms (ACO, PSO, Artificial Bee Colony, Glowworm Swarm Optimization) in crowd evacuation scenarios with different spatial configurations, population density, and number of exits [11]. Their results show that modified and hybrid versions of SI algorithms consistently outperform the baseline algorithms in terms of evacuation time, convergence to the optimal solution, and resistance to local minima. This is especially noticeable in dense configurations with many exits and obstacles, where standard algorithms often get stuck in suboptimal solutions due to local clustering of agents.

Sun et al. (2025) proposed EPIACO (Enhanced Path Planning Improved Ant Colony Optimization), a modified ACO with six key improvements: a dynamic pheromone trap to prevent premature convergence, adaptive heuristic parameters to balance exploration and exploitation, node congestion penalties, and real-time pheromone update mechanisms. In a series of tests on static and dynamic networks (including bandwidth variations, unexpected obstacles, and output state changes), EPIACO showed significantly faster convergence and better global solutions compared to standard ACO, classical pathfinding algorithms (Dijkstra,

A*), and other SI approaches. Most importantly, the algorithm works effectively under uncertainty, making it suitable for real-time navigation systems during emergencies [12].

While optimization-centric research focuses on identifying ideal evacuation routes, complementary studies investigate crowd dynamics through behavior-based and agent-based models. Escape Algorithm, for example, is trying to replicate the full spectrum of human reactions – from calm movements to panic and chaotic crowding [13], [14]. Such models provide valuable behavioral insights but they come at the cost of high computational complexity, which makes them insufficient for decision-making, performed in real-time. This limitation emphasizes the importance of swarm intelligence algorithms: they quickly build efficient evacuation routes without neglecting real infrastructure constraints.

Li et al. (2026) developed an integrated model combining an artificial bee colony (ABC) with cellular automata and a hydrodynamic model to simulate pedestrian evacuation during floods in urban environments. They explicitly modeled the capacity of streets, squares and exits, as well as the dynamics of water that impedes movement. Experiments showed that the configuration of exits and crowd density critically affect the overall evacuation time: multi-exit scenarios with distributed load reduce evacuation time by 30-40% compared to single-exit scenarios. They also found that the ABC algorithm with dynamic congestion penalties better balances time minimization and congestion avoidance, which directly confirms the importance of capacity-aware objective functions in SI for evacuation [15].

Alazbah et al. (2023) use Multi-Agent Systems (MAS) models in NetLogo to simulate individual and collective human behavior in hazardous environments (fires, floods, terrorist threats). They emphasize that understanding human behavior in stressful scenarios (panic, social pressure, imitation, irrational decisions) is critical for developing effective evacuation strategies, but such models have high computational cost due to the large number of agents and complex interactions between them. The authors propose a combined approach: using MAS for detailed behavioral analysis and SI algorithms for fast real-time optimization planning, which resonates with the approach of capacity-aware optimization as a practical guide for evacuation [16].

Du (2024) developed an optimized method for emergency evacuation route planning using an iterative bio-inspired heuristic algorithm that constructs paths from the disaster area to each shelter location. The method is designed to distribute traffic flow with efficient evacuation planning, considering travel time as a key parameter, as well as considering conflicting spatial objectives and constraints in multi-criteria optimization. The authors emphasize that traditional optimization methods are inconvenient for such complex problems, and meta-heuristics (in particular, bio-inspired algorithms) show efficient solutions, which confirms the relevance of the SI approach for urban evacuation [17].

A separate important direction in the field of spatial optimization is the development of intelligent internal navigation systems for complex architectural complexes. In particular, the study by Lysenko and Lobanchykova proposed a graph method for tracking and virtual accompaniment in medical institutions, where the analysis of modern heuristic approaches (in particular, the particle swarm algorithm – PSO) confirmed their high efficiency for increasing localization accuracy [28]. At the same time, such solutions are focused mainly on individual routing of users and calculating the shortest path in conditions of isolated traffic. In conditions of mass emergencies, such an approach turns out to be limited, since it ignores the nonlinear dynamics of crowd formation and the risks of critical overload of exits.

Finally, research on multi-robot-assisted evacuation shows an interesting result: even a small number of autonomous robots can influence large crowds through local interactions and adaptive navigation strategies [18]. This result is very similar to the main finding in the present study: a well-designed, capacity-aware optimization algorithm can serve as a successful guidance to safe evacuation of complex human systems, if physical limits of the infrastructure are considered.

RESEARCH AIM AND OBJECTIVES

The object of research is the evacuation process in complex buildings with multiple exits, which is considered as a flow distribution problem with capacity constraints. Particular attention has been paid to the interplay between crowd movement and

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architectural limitations, such as exit capacity throughput.

The subject of research is development and comparison of metaheuristic optimization algorithms, specifically Modified Particle Swarm Optimization (PSO_MI) and Enhanced Ant Colony Optimization (ACO_EH), for improving the evacuation-route assignment in heavily congested scenarios.

The purpose of the research is to design and validate the swarm intelligence model that allows for the effective distribution of flows of people between exits, while taking into account their throughput capacity, and decrease of the total evacuation time.

To achieve this purpose, the following main research objectives were pursued:

1) to develop a non-linear objective function with penalties to simulate real-world bottleneck formation;

2) to tune the parameters and modify swarm algorithms to improve their global search capabilities in high-congestion environments;

3) to evaluate algorithms efficiency in different heavily overloaded building scenarios;

4) to determine the trade-off between optimality and statistical stability to select the most robust algorithm for practical application.

METHODS

The study applies a systematic approach to examine how Swarm Intelligence can be employed for emergency evacuation route planning in capacity-constrained environment. The research process is based on conceptual analysis and computational simulation.

The choice of metaheuristic methods, in particular the ant colony algorithm (ACO) and particle swarm optimization (PSO), is justified by their proven effectiveness in solving complex problems of spatial coordination and dynamic routing. Modern research in the field of intelligent systems, in particular the work of Al-Behadili et al. [25], confirms that the synergistic application of ant and flocking strategies (Flocking/PSO) allows for the successful optimization of the trajectories of groups of autonomous agents in spatially constrained environments.

Ant Colony Optimization. Ant Colony Optimization (ACO) has been increasingly applied to solve evacuation problems, which aim to model and optimize pedestrian movement in confined spaces during emergency. Inspired by how real ants search for food, ACO provides a framework for representing the route selection of each agent (pedestrian), their response to the surrounding environment, and their adaptation to dynamic hazards. The pheromone mechanism reflects accumulated knowledge about safe or efficient paths, allowing for emergent collective behavior that reflects real-world evacuation scenarios.

This approach is based on how ant colonies work in nature. Although an individual ant is a simple creature with limited capabilities, the coordinated behavior of the colony leads to efficient solutions to complex problems. Typical applications include finding the shortest routes between two points. Their interactions are indirect and self-organized, because ants do not require direct communication with each other – a process commonly referred to as stigmergy [19]. Such mechanisms form the conceptual basis for applying ACO to evacuation modeling.

At its core, of the algorithm is simple. Initially, ants are randomly placed on the nodes of the graph, and the pheromone on each edge is initialized to the same value:

$$\tau_{ij}(0) = \tau_0. \quad (1)$$

Each ant then selects the next node to visit according to a probabilistic decision rule. The chance that ant k goes from node i to node j is calculated as:

$$P_{ij}^k(t) = \frac{(\tau_{ij})^{\alpha} \cdot (\eta_{ij})^{\beta}}{\sum_{s \in N_i^k} (\tau_{is})^{\alpha} \cdot (\eta_{is})^{\beta}}, \quad (2)$$

where τ_{ij} is the pheromone level on edge (i,j), $\eta_{ij} = \frac{1}{d_{ij}}$ is the heuristic value based on the distance d_{ij} between nodes, α and β are parameters that control the relative influence of pheromone versus heuristic information, and N_i^k is the set of nodes that ant k can visit next [20].

After all ants complete their routes in iteration t, the length of each path is evaluated, and the shortest path is stored.

The pheromone levels on the edges are then updated using the following rules:

1. Pheromone evaporation:

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij}, \quad (3)$$

where ρ is the evaporation rate, which prevents unlimited accumulation of pheromones and encourages exploration.

2. Pheromone disposition:

$$\tau_{ij} \leftarrow \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^k, \quad (4)$$

$$\Delta\tau_{ij}^{k} = \begin{Bmatrix} \frac{Q}{L^{k}(t)}, if\ an\ ant\ k\ used\ edge\ (i,j) \\ 0, otherwise \end{Bmatrix}, \quad (5)$$

where L^k is the total length of the path traveled by ant k and Q is a constant representing the total pheromone deposited.

Through repeated iterations, these updates guide the search toward shorter paths while still allowing exploration of alternative routes. Over time, the algorithm converges toward an optimal or near-optimal solution [20], [21].

Despite the universality of the classical ant colony algorithm, its basic mathematical formulation often has a tendency to premature convergence and inefficient search under hard constraints. To overcome these shortcomings, specialized modifications of ACO operators are actively being developed in modern research. In particular, Khudov et al. proposed a modified method based on the elite ant algorithm for forecasting and optimizing routes of aviation complexes in difficult environments [26].

Following the concept of improving the search ability of agents, this study developed an original version of the algorithm – Enhanced Ant Colony Optimization (ACO_{EH}). Unlike the method proposed by Khudov et al., which focuses on selecting elite routes for traffic prediction, our approach changes the internal parameters of the heuristic information of the ants themselves. Combined with a new nonlinear penalty function, this gives the algorithm the ability to "see" potential traffic jams and quickly redirect people flows to bypass congested exits.

Particle Swarm Optimization. Particle Swarm Optimization (PSO) is another swarm intelligence metaheuristic that has been widely applied to optimization problems, including path planning and evacuation modeling. Unlike ACO, which is based on stigmergic communication via pheromones, PSO is inspired by a completely different phenomenon – the coordinated movement of flocks of birds, schools of fish or crowds of people.

The main idea is that individual particles adjust their trajectories by combining their own experience with the results of the most successful members of the swarm. By working together, the swarm can explore most of the areas of the search space, often very efficiently.

This approach is based on the biological observation that animal groups move in coordination without centralized control. Each individual follows simple rules: keep moving in the same direction, be attracted toward neighbors, and avoid collisions. Technically, each particle is a potential solution to the given problem and its position is adjusted according to both its personal best performance and the best performance achieved by the swarm [22], [23].

The PSO algorithm looks for solutions in a continuous search space – imagine a flock of birds collectively searching for the best place to roost. At the beginning, the swarm of N particles is initialized with random positions $x_i(0)$ and velocities $v_i(0)$, where $i = 1, \dots, N$. Each particle "remembers" its personal best position so far (p_i) and the best position (g) found by the entire swarm.

At each time step t the velocity and position of a particle i are updated according to the formulas:

$$v_i(t+1) = \omega v_i(t) + c_1 r_1\big(p_i - x_i(t)\big) + c_2 r_2(g - x_i(t)), \quad (6)$$

$$x_i(t+1) = x_i(t) + v_i(t+1), \quad (7)$$

where ω is the inertia weight that is responsible for the fact that most particles "remember" their previous direction of movement; c_1 is the cognitive coefficient, which pulls the particles back to its own best experience; c_2 is the social coefficient, reflecting attraction toward the swarm's best-known solution so far; finally r_1 and r_2 are random numbers evenly distributed in [0,1], which introduce variability into the search process.

The balance between these components is the key point in the algorithm. It will determine if the swarm will start exploring new regions or focus on already found promising solutions. A large ω promotes further exploration of search space, while smaller value makes particles stick to the found solutions so far. Similarly, high c_1 makes particles more autonomous and independent, whereas high c_2 turns the swarm into a cohesive team.

With each iteration, particles gradually converge toward better regions of space – the ones that may provide solutions with higher quality. Eventually, the swarm finds the optimal or almost optimal result, while the random factors ensure that the possibility of finding other better options still remains [23], [24].

Due to its fast computation and flexible local search capabilities, the classical PSO algorithm is one of the most popular tools for finding the shortest routes in dynamic networks, as evidenced by its successful integration into modern hybrid control systems [27].

However, in its standard form, this algorithm optimizes traffic without considering the capacity of nodes. Unlike autonomous vehicle logistics [27], where obstacle avoidance is key, the mass evacuation planning problem requires strict adherence to capacity limits. That is why in this work, a modification of PSO_{MI} was developed,

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where the basic parameters are adapted through a nonlinear penalty objective function

Graph representation. The physical layout of the target structures (high-rise, shopping mall, and hospital) is modeled as an undirected, unweighted graph, $G = (V, E)$, where V is the set of vertices (nodes) and E is the set of edges (connections). This turns the evacuation problem into finding the best way to move people through a network.

Vertices (V): The set of vertices V is divided into two distinct subsets:

– Rooms (V_R): these include all indoor spaces, such as offices, shops, or hospital wards, which are initially occupied by people. Each room $i \in V_R$ is given an initial number of people (P_i). Rooms are color-coded from orange to red, where the deeper red indicates higher occupancy (see Fig. 1, Fig. 2 and Fig.3).

– Exits (V_E): these are the safe points through which the people can leave the building. Each exit $j \in V_E$ has a limited capacity (C_j), meaning it can only let a certain number of people through at a time. Exits are marked in green on the diagrams, and, similarly to rooms, the color depth indicates their throughput capacity which is also shown with numbers for better clarity (Fig.1, Fig.2 and Fig.3).

Edges (E): the edges connect vertices to each other and correspond to real-world paths such as corridors or stairs. Since the graph is undirected, movement is possible in both directions. All paths are considered equivalent, so the graph is unweighted. It means that the route length $L_{i,j}$ is calculated simply as the number of transitions between the nodes from the room i to the exit j.

This abstraction significantly simplifies the model, while allowing us to focus on the most important thing – exit overload and throughput capacity constraints. In other words, what is crucial here is not how far away the exit is, but how many people it can accommodate and how to evenly distribute the flow.

Fig. 1 illustrates the graph of a high-rise building: 20 room nodes are distributed across three floors and connected by sequential edges within each floor, modeling horizontal corridors, while inter-floor transitions are represented by edges acting as stairwells. Three exit nodes are located exclusively on the ground floor, creating natural topological bottlenecks in the graph.

Fig. 2 illustrates the graph of a shopping center: 24 room nodes are distributed across four sections connected by corridor nodes, with each section featuring a single exit having a specific throughput capacity. This structure was selected because it models the typical layout logic of large shopping complexes, where stores are grouped into wings or zones with separate evacuation exits.

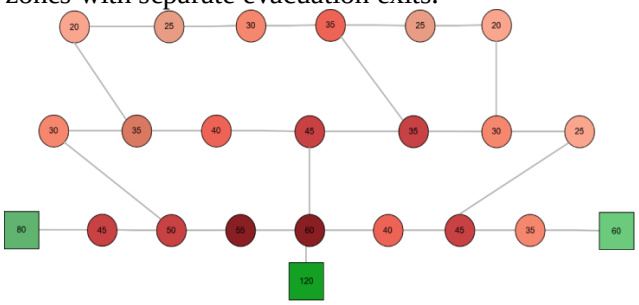


Fig 1. **Graph representation of the High-rise building**

***Source*: compiled by the authors**

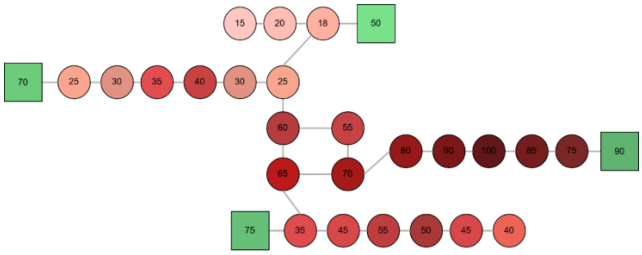


Fig. 2. **Graph representation of the Shopping mall**

***Source*: compiled by the authors**

Fig. 3 shows the graph of the hospital building: 15 room nodes are organized into two wings connected by a central corridor node; both exits are located at opposite ends of the central corridor. It corresponds to the actual corridor layout of hospital buildings, where a minimal number of exits is typical due to safety and patient room isolation requirements, making this scenario the most demanding in terms of algorithm stability.

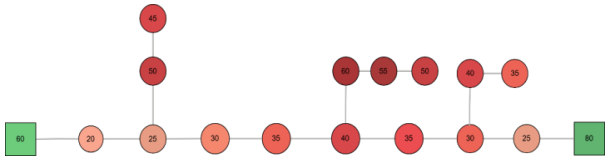


Fig. 3. **Graph representation of the Hospital**

***Source*: compiled by the authors**

The Enhanced Congestion Objective Function. The objective of the evacuation optimization is to find an assignment function $A: Rooms\ (V_R) \rightarrow Exits(V_E)$ which assigns every room i to exactly one exit j. The performance of this assignment is evaluated by minimizing the Total Weighted Evacuation Time (T_{total}).

T_{total} is the sum of the effective evacuation times ($T_{effective}$) weighted by the population (P_i), calculated as:

$$T_{total} = \sum_{i \in V_R} P_i \cdot T_{effective}(i,j)$$

The objective function incorporates three non-linear penalties – congestion factor, congestion penalty, overflow penalty – to realistically model bottlenecks when the total assigned load L_j^{total} exceeds an exit's capacity C_j.

The total effective time for a room i evacuating to exit j is calculated by the formula:

$$T_{effective}(i,j) = L_{i,j} \cdot (1 + CF) + CP + OP$$

The main complexity arises from three non-linear penalties applied to the effective time ($T_{effective}$). Together, they prioritize exit throughput capacity (C_j) over simple distance.

The congestion factor (CF) is defined as the square of the ratio of the current load on the exit to its throughput: $CF = \left(\frac{L_j^{total}}{C_j}\right)^2$. It quadratically increases the base travel time $L_{i,j}$ as the exit load (L_j^{total}) approaches capacity.

Congestion penalty (CP): $CP = 50 \cdot CF$. Even if the capacity is not technically exceeded, this large cost term that ensures load balancing is favored. It forces the algorithm to distribute flows more evenly.

Overflow penalty (OP) only comes into effect when the load exceeds the throughput ($L_j^{total} > C_j$): $OP = 10 \cdot \left(0, L_j^{total} - C_j\right)^2$. Its value increases drastically at the slightest excess of a limit. This massive penalty forces the optimization algorithms to treat capacity limitations as a strict prohibition.

All the penalty coefficients were chosen empirically to ensure that capacity violations dominate distance minimization in terms of the objective function value, while keeping the computation numerically stable.

In their standard formulations, PSO and ACO typically employ moderate inertia weights ($\omega \approx 0.4–0.7$), heuristic influence values ($\beta \approx 1–2$), and pheromone evaporation rates ($\rho \approx 0.5$). However, these default settings often perform poorly in evacuation problems characterized by steep, non-linear capacity constraints and deep local minima.

To optimize performance in this complex, high-penalty landscape, the standard Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) algorithms were modified and henceforth denoted as Modified PSO (PSO_{MI}) and Enhanced ACO (ACO_{EH}). New parameter values were selected based on previous experiments and existing research in the field of congestion-aware swarm optimization. They are presented in Table 1.

Table 1. **Parameters of the modified swarm optimization algorithms**

Algorithm	Parameter	Value
Modified PSO (PSO_{MI})	Inertia weight (ω)	0.9
Enhanced ACO (ACO_{EH})	Heuristic influence (β)	3.0
	Evaporation rate (ρ)	0.3

***Source*: compiled by the authors**

In the modified PSO variant (PSO_{MI}), the inertia weight ω was set to 0.9. This relatively high value increases global exploration by making particles maintain their direction of motion for longer time. As a result, the swarm is less likely to get stuck in local minima, which may often occurs in evacuation problems due to sharp and nonlinear congestion penalties.

Two parameters were adjusted for the enhanced ACO variant (ACO_{EH}). First, the heuristic influence β was increased to 3.0. A higher value for this parameter means that the algorithm leans more on heuristic guidance. It helps ants find routes that are both shorter and can lead to the exits with sufficient throughput. This allows them to determine good directions more effectively right from the start.

Secondly, the pheromone evaporation rate ρ was reduced to 0.3. It means that the pheromone remains on successful routes for a longer period of time. Because of that, the algorithm remembers good solutions better and returns to them more often. This makes the search process more stable and predictable.

Simulation setup and test scenarios. To evaluate the proposed algorithms, three representative building templates – a high-rise, a shopping mall, and a hospital – were designed based on common architectural patterns reported in evacuation and crowd management studies. These abstracted layouts, shown as graph representations in Fig.1 Fig.2 and Fig.3, reflect typical multi-floor, corridor-based structures, which can be found in real-world public buildings. Although simplified, the models intentionally keep important structural features such as corridors and exit capacity constraints. This ensures a realistic and controlled environment for evaluating evacuation strategies, which account for limited capacity.

The complexity of the scenarios is due to high capacity utilization, architectural bottlenecks, and uneven exit capacities.

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The high-rise building includes 20 rooms on three floors and three exits with capacities of 80, 120, and 60 occupants. With a total population of 725, this result in a capacity utilization of 278.8 %, this represents extreme congestion.

The shopping mall consists of 24 rooms arranged around a central courtyard, with four exits of capacities 70, 50, 90, and 75 people. With a total population of 1,188, these results in a capacity utilization of 416.8 %, this makes it the most overloaded scenario.

The hospital scenario simulates a corridor-branch layout with 15 rooms and two exits with capacities of 60 and 80 occupants, serving 575 people and providing a capacity utilization of 410.7 %.

Together, these scenarios combine uneven exit capacities, population imbalances, and architectural bottlenecks, creating highly challenging optimization problems. The Shortest Path heuristic, which assigns occupants to the nearest exit without considering congestion or capacity constraints, serves as a baseline for testing the effectiveness of the proposed swarm intelligence algorithms.

Three test scenarios – high-rise, shopping mall, and hospital – are built on the abstract graph representations, shown in Fig.1, Fig.2 and Fig.3.

RESEARCH RESULTS

Algorithm performance comparative analysis. Table 2 presents the mean total weighted evacuation time (T_{total}) for the Shortest Path Baseline and the two modified swarm intelligence algorithms across three distinct building scenarios. The Shortest Path Baseline is deterministic; therefore, repeated runs yield identical results ($\sigma = 0$).

The baseline shortest-path approach is deterministic and yields identical results with each run ($\sigma = 0$), as it lacks a stochastic component. In contrast, both swarm algorithms exhibit some variability in results due to random initialization, reflected in non-zero standard deviation values. Notably, σ varies significantly across scenarios; the biggest contrast is observed in the hospital case, where ACO_{EH} achieves near-perfect reproducibility ($\sigma = 25.170$), whereas PSO_{MI} demonstrates considerably higher variability ($\sigma = 681.124$) – reflecting a fundamental difference in the search strategies of the two algorithms under conditions of strict capacity constraints.

Absolute values of T_{total} are quite large due to the penalty applied for overcrowding, so the main indicators of efficiency here are the relative improvements.

The results consistently demonstrate that both modified swarm intelligence algorithms significantly outperform Shortest Path Baseline approach in all the proposed scenarios.

On average, the PSO_{MI} algorithm achieved a 34.58 % reduction in the total weighted evacuation time compared to the Baseline, while ACO_{EH} reached a 33.66 % improvement.

It is worth noting that the overall average improvement (34.58% for PSO_{MI} and 33.66 % for ACO_{EH}) is significantly lower than the result of the high-rise (54.95 %) which is explained by the lack of bandwidth in the mall and hospital scenarios. With utilization of 416.8 % and 410.7 %, respectively, no route configuration is able to completely eliminate exit congestion – the algorithms minimize the penalty term, but cannot overcome the structural discrepancy between the number of evacuees and the total capacity of the infrastructure. On the other hand, a high-rise building with a utilization of 278.8 % leaves more space for the redistribution of flows between exits, which causes a much higher improvement rate. This emphasizes an important practical conclusion: the effectiveness of route optimization algorithms is fundamentally limited by the architectural characteristics of the building, and improving evacuation safety requires both algorithmic and infrastructural solutions.

Table 2. **Average evacuation times and performance improvement**

Building Type	**Baseline**	PSO_{MI}	ACO_{EH}	**PSO Improvement**	**ACO Improvement**
High-rise	109,604,596.84 ± 0	49,375,684.51 ± 151,121	49,507,152.58 ± 165,190	54.95 %	54.83 %
Shopping Mall	302,824,212.07 ± 0	224,814,000.95 ± 2,100,861	230,759,838.75 ± 2,119,302	25.76 %	23.80 %
Hospital	117,239,670.38 ± 0	90,242,151.71 ± 681,124	91,087,060.79 ± 25,170	23.03 %	22.31 %
Overall Avg	176,556,159.76	121,477,279.06	123,784,684.04	34.58 %	33.66 %

***Source*: compiled by the authors**

The baseline approach's inability to account for capacity constraints led to critical overcrowding – confirming that the high objective function values stem primarily from nonlinear penalties for exceeding capacity. The swarm algorithms' strength lies in their ability to globally optimize flow distribution and thereby minimize these penalties. A comparison of results is shown in Fig. 4. A lower bar indicates a better result. The height of the bar for the baseline approach (Shortest Path) clearly illustrates the extent of exit congestion that arises when throughput capacity is ignored: the algorithm concentrates the entire flow on the nearest exits, causing a quadratic increase in the penalty terms within the objective function. The difference in height between the baseline bar and the bars for PSO_{MI} and ACO_{EH} visually demonstrates the effectiveness of the load-balancing mechanism; the greater this difference, the more critical the role of accounting for throughput capacity is for the given topology.

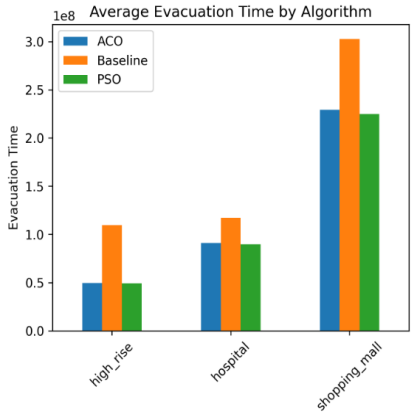


Fig. 4. **Comparative analysis of Total Weighted Evacuation Time**
***Source*: compiled by the authors**

The high-rise building scenario produced the best results. Both algorithms – PSO_{MI} and ACO_{EH} – achieved roughly 55 % improvement. The large 54.95 % reduction achieved by PSO_{MI} demonstrates the success of the high inertia parameter ($\omega = 0.9$). In a multi-story building with several exits, the modified algorithm was able to thoroughly explore the search space and find the right balance – notably by redirecting flows away from the lowest-capacity exit (60 people) toward a medium-capacity one (120 people), which was located farther from most rooms.

The shopping mall scenario proved to be the most challenging, combining the largest crowd size and the highest load levels. The PSO_{MI} maintained its lead with a 25.67 % improvement, while the ACO_{EH} reached 23.80 %. Here, PSO_{MI}'s capacity for global search played a decisive role. With severe overcrowding and four exits of varying capacities, the problem structure was highly complex. PSO_{MI} was better at uncovering non-obvious solutions that made full use of all exits and distributed flows more evenly.

The hospital scenario – with only two exits and a total capacity of 140 people – highlighted the difference in algorithmic reliability. Although PSO_{MI} achieved a slightly better average result (23.03 % improvement), the ACO_{EH} produced far more consistent outcomes, with a standard deviation (σ) of just 25.170 compared to PSO_{MI}'s deviation of 681.124.

The ACO_{EH}'s stability is directly due to its modifications: the high heuristic influence ($\beta = 3.0$) and low evaporation ($\rho = 0.3$) allowed it to quickly identify and reinforce the small set of efficient routes connecting 15 rooms to two exits. This demonstrates that for systems with tight constraints and high safety demands – hospitals being the clearest example – the Enhanced ACO delivers more reliable results and reduces the risk of evacuation failure.

Based on the quantitative results we came to the following conclusions:

1) For optimality and speed the Modified PSO_{MI} is the superior choice since it achieved the lowest mean evacuation time and the highest overall improvement (Table 1). Its high inertia proved effective in finding the global optimum in the complex, heavily penalized search space.

2) For reliability in severe constraints the Enhanced ACO_{EH} demonstrated greater statistical consistency (low σ) in the hospital scenario. In systems where solution stability is critical, the ACO_{EH}'s strong load-balancing capability makes it the preferred choice.

Algorithm robustness and statistical consistency. Statistical consistency is particularly important for evacuation planning systems because it shows how consistently the algorithm produces similarly strong results when starting from different random initial conditions. For this purpose, the standard deviation (σ) of the results from ten runs was used in this paper.

The most telling result regarding algorithm consistency was obtained in the hospital scenario, where capacity throughput constraints were the harshest. In this case, ACO_{EH} showed very high stability. Standard deviation was only 0.03 % of the mean score, which means that results are almost

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perfectly reproducible. This can be explained by how the ACO_{EH} algorithm is designed: combination of strong heuristic influence ($\beta = 3.0$) and slow evaporation rate ($\rho = 0.3$) allows it to quickly settle on one reliable, well-balanced flow distribution.

The PSO_{MI} showed considerably more variability in the same scenario ($\sigma = 681.124, or\ 0.75\%\ of\ the\ mean\ score$). This is quite logical since high inertia weight ($\omega = 0.9$) forces swarm to actively explore different solution options. Although on average PSO_{MI} algorithm delivered the best result, such exploratory behavior sometimes led to slightly less optimal solutions, and that, in return, results in higher penalties for overloading.

The results suggest a clear trade-off. PSO_{MI} is better at hunting down the optimal solution and produces the lowest average objective function values. However, the ACO_{EH} is significantly more consistent and delivers more predictable results, which is especially important in conditions with high limitations, such as hospitals. From a practical standpoint, often stability is preferred for systems. Therefore, in such environments ACO_{EH} can be a more reliable choice, despite having slightly less optimal solutions sometimes.

To provide further quantitative confirmation of solution stability, the coefficient of variation ($CV = \sigma/\mu$) was calculated for each algorithm and building scenario. Across all configurations, the CV did not exceed 1 %, reaching a maximum of 0.93 % for PSO_{MI} in the shopping mall scenario and a minimum of 0.03 % for ACO_{EH} in the hospital scenario. This confirms that both algorithms ensure high result reproducibility, regardless of random initialization. Low CV values are particularly significant in the context of evacuation planning, where the reliability and predictability of route assignments are critical system requirements.

Convergence Behavior and Computational Efficiency. The last part of comparative analysis focuses on the convergence speed of the algorithms and computational costs. While the primary goal of evacuation modelling is to find an optimal solution ahead of time – in offline mode – real emergencies can demand rapid route recalculation on the fly. In those moments, how fast the algorithm runs matters just as much as how good the answer is.

Convergence Behavior. Both algorithms demonstrated similar overall behavior. The biggest improvements happened within the first 20 iterations. This is important as it means that both approaches figure out the structure of the problem quite quickly and avoid the problematic solutions, which lead to severe penalties due to overloading. It shows that the search strategies – specifically, the enhanced heuristic ($\beta = 3.0$) in ACO_{EH} and the strong global best attraction in PSO_{MI} – effectively move through the non-linear objective function and quickly avoid the large penalties caused by poor initial load distribution.

After approximately iteration 20, the convergence process slows down. Algorithms no longer make abrupt changes and move to gradually refining solutions. PSO_{MI} behaves more smoothly as it continues to explore alternatives due to inertia ($\omega = 0.9$). At the same time, ACO_{EH} finds good solution faster due to pheromone reinforcement and is less active in changing the routes it finds.

Fig. 5 illustrates the convergence characteristics of both algorithms across building types over 100 iterations:

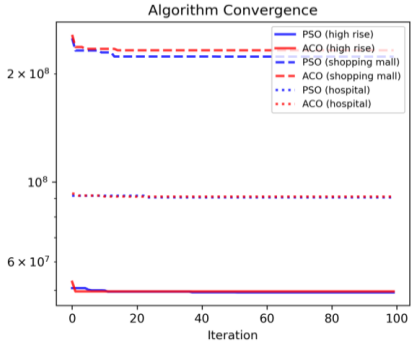


Fig. 5. **Iterative convergence of modified swarm algorithms**
***Source*: compiled by the authors**

The characteristic shape of the convergence curves – a sharp drop in the objective function value during the first 20 iterations followed by a transition to a plateau – is a direct consequence of the penalty function's nonlinear structure. Since the CF and OP terms grow quadratically with output overload, even a slight redistribution of flows between outputs during early iterations drastically reduces the total penalty, resulting in the steep initial decline. By the plateau stage, the algorithms have already avoided critical overloads and are merely making adjustments to flow distribution within permissible load limits, where the objective function changes more slowly. The PSO_{MI} curve is smoother throughout the process due to high inertia ($\omega = 0.9$), whereas the ACO_{EH} curve stabilizes more quickly thanks to pheromone reinforcement of the best routes – a distinction particularly evident in topologies with a limited number of outputs, such as a hospital.

Computational Efficiency. Table 3 details the average computation time required to execute 100 full iterations for each algorithm.

Table 3. **Average computation times per scenario**

Algorithm	High-rise	Shopping Mall	Hospital	Average
Baseline	0.001s	0.001s	0.001s	0.001s
PSO_{MI}	0.405s	0.579s	0.292s	0.425s
ACO_{EH}	2.306s	3.458s	1.429s	2.398s

***Source*: compiled by the authors**

The PSO_{MI} algorithm was consistently and significantly faster than ACO_{EH}. On average it runs in about 0.425s, which is approximately 5.6 times faster. This is because PSO uses relatively simple mathematical operations to update particle positions. In contrast, ACO is more computationally "heavy" because it requires constant updating of pheromones and calculation of probabilities for each step.

An analysis of computation times across the different scenarios reveals a pattern directly linked to the graph size. The hospital scenario is the fastest for both algorithms (PSO_{MI}: 0.292s, ACO_{EH}: 1.429s), as the graph – comprising 15 rooms and only two exits – significantly limits the number of possible flow distribution combinations. Conversely, the shopping mall scenario is the most computationally intensive (PSO_{MI}: 0.579s, ACO_{EH}: 3.458s); the larger graph, featuring 24 rooms and four exits with varying capacities, expands the search space and necessitates a greater number of objective function evaluations. Notably, ACO_{EH} operates 2.4 times slower for the shopping mall than for the hospital, whereas the difference for PSO_{MI} is only twofold; this indicates that ACO is more sensitive to problem size, as the updating of pheromone trails and the recalculation of transition probabilities are performed for every graph edge during each iteration.

Sensitivity analysis of key algorithm parameters. To assess the robustness of the obtained results with respect to parameter selection, a sensitivity analysis was conducted for three key parameters of the modified algorithms: the ACO pheromone importance coefficient (α), the ACO pheromone evaporation rate (ρ), and the PSO inertia weight (ω). In addition to that, the influence of the overflow penalty weight coefficient in the objective function was examined. For each parameter three levels were tested – lower, baseline, and higher, – while keeping the other ones at their baseline values. Each configuration was evaluated over 10 independent runs for each of the three building scenarios. The results are summarized in Table 4 and Table 5.

Table 4. **Sensitivity analysis for ACO**

Parameter	Value	High-Rise	Mall	Hospital
α	0.5	53.99 %	23.24 %	21.94 %
	1.5	**54.98 %**	**23.62 %**	**22.31%**
	3.0	54.82 %	24.08 %	22.19 %
ρ	0.1	54.99 %	25.10 %	22.34 %
	0.3	**54.98 %**	**23.62 %**	**22.31%**
	0.6	54.82 %	23.41 %	22.00 %
OP multiplier	1	54.31 %	23.65 %	21.94 %
	10	**54.98 %**	**23.62%**	**22.31%**

***Source*: compiled by the authors**

The influence of pheromone importance coefficient (α). At $\alpha = 0.5$, the algorithm gives more weight to the heuristic distance estimate than to the pheromone trail, which leads to the lowest improvement rates among all configurations: for the skyscraper – 53.99 %, the shopping center – 23.24 %, the hospital – 21.94 %. At the same time, the results at $\alpha = 0.5$ are the most stable ($\sigma = 32.893$ for the skyscraper, $\sigma = 6.735$ for the hospital), which is explained by a more deterministic choice of routes under the influence of the heuristic. At $\alpha = 3.0$, the influence of the pheromone trail increases, which for the shopping center gives the best result among all α (24.08 %), but for the skyscraper and the hospital there is a slight degradation (-0.16 pp and -0.12 pp, respectively) due to excessive fixation of agents on early suboptimal routes. The baseline $\alpha = 1.5$ provides the best average across the three scenarios and is the most balanced between search and anchoring.

The influence of pheromone evaporation coefficient (ρ). This parameter directly controls the duration of collective route memory retention. At $\rho = 0.1$, agents retain information about secondary paths longer, which is especially important for a shopping mall with four uneven exits: the improvement in ACO_{EH} reaches 25.10 % versus 23.62 % of the baseline – the best result for ACO among all ρ configurations. At the same time, a lower evaporation rate increases the computational time: for a shopping mall at $\rho = 0.6$, the calculation time increases to 5.451s versus 3.615s for the baseline $\rho = 0.3$ (+51 %), and for a hospital – to 3.067s versus 2.639s (+16 %). Accelerated evaporation at $\rho = 0.6$ causes a sharp increase in instability: the standard deviation of ACO_{EH} for the

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hospital scenario increases by a factor of 17.7 – from $\sigma = 25.170$ at $\rho = 0.3$ to $\sigma = 446.338$ at $\rho = 0.6$ – due to the algorithm losing connection with previously detected balanced routes. For a high-rise building, where the problem structure is less sensitive to the choice of ρ, changing the parameter gives only 0.17 pp. of variance, confirming the topological dependence of the sensitivity.

Table 5. **Sensitivity analysis for PSO**

Parameter	Value	High-Rise	Mall	Hospital
ω	0.4	54.83 %	25.40 %	22.63 %
	0.7	55.01 %	25.56 %	22.81 %
	0.9	**54.97 %**	**25.76 %**	**23.03 %**
OP multiplier	1	54.36 %	25.10 %	22.94 %
	10	**54.97 %**	**25.76 %**	**23.03 %**

***Source*: compiled by the authors**

Limitations. Although the results look promising, it is worth noting the actual limitations of our approach. Firstly, the building layouts were created synthetically and presented as undirected unweighted graphs. This abstraction does take into account key architectural bottlenecks and constraints, yet it certainly misses out on such important things as variations in corridor widths, people speed and dynamic hazards like smoke or blocked exits.

Secondly, this model considers population as a static object, ignoring human emotions and behavior psychology. In real cases, panic, fear, inability to comply with instructions or group dynamics can drastically change the course of events. Our approach fails to capture these kinds of things.

Also, the throughput capacity of exits and corridors in the proposed model is a fixed constant, whereas in actual emergency situations, it may change dynamically due to the partial obstruction of exits by smoke or fire, crowd congestion at bottlenecks, or damage to structural elements of the building. Ignoring this dynamic implies that the optimal route distribution determined by the algorithm may prove suboptimal or unfeasible in real-world conditions, where infrastructure capacity degrades during the evacuation process.

Another limitation is that the developed algorithms have been validated exclusively on synthetic graph models. Testing on real building BIM models requires an additional technical stack – specifically, tools for parsing IFC files, converting architectural geometry into a graph structure, and integrating with pedestrian movement simulators – which constitutes a substantial, independent task that lies beyond the scope of this study, but still is a promising direction for future research.

And lastly, the evacuation planning process is performed "offline". We assume that there is a full building topology available as well as the knowledge of population distribution prior to an emergency event. This approach is appropriate for creating pre-planned evacuation strategies and intelligent building management systems. However, if the goal is the evacuation planning that is possible to carry out in real-time, the system must be able to process data from sensors on the go and modify the strategy in conditions of full uncertainty.

Practical Implications. The results of this research demonstrate high potential for two modified swarm intelligence algorithms – PSO_{MI} and ACO_{EH} – for leveraging in evacuation planning in cases of real emergencies. The algorithms achieved substantial and life-saving improvements over traditional nearest-exit strategies, by addressing the critical issue of exit capacity saturation.

Both approaches significantly outperform the shortest path principles by reducing overall evacuation delays up to 55% in the given scenarios. It confirms that incorporating penalties for exceeding exit capacities is actually effective. This approach makes algorithms distribute people in a more even manner, rather than focusing solely on finding the shortest route, which is critically important in real emergency conditions.

From a practical standpoint, the choice between the two algorithms depends on the primary goal of the system. Modified PSO (PSO_{MI}) is faster in computation and finding the most optimal solution. It consistently delivers the best routes and performs calculations in less than half a second. This makes it especially suitable for dynamic situations, where conditions change quickly and fast decision-making is required.

The Enhanced ACO (ACO_{EH}) focuses on stability and reliability. It demonstrates results of the same quality after multiple runs and proves to be particularly effective in heavily constrained environments, such as hospitals. Therefore, it is more appropriate to use it in pre-designed critical systems.

In terms of practical integration, the developed algorithms can function as a route optimization module within modern BIM platforms (such as Autodesk Revit and ArchiCAD). The module takes the building's graph topology and exit capacity characteristics – automatically exported from an IFC file – as input and generates an optimal evacuation flow distribution plan. Within the context of

building digital twins, these algorithms can aggregate real-time data on room occupancy from IoT sensors and rapidly recalculate routes in response to changing operational conditions. The PSO_{MI} calculation time of less than 0.5 seconds makes such dynamic adaptation technically feasible while an emergency situation is unfolding.

Overall, both algorithms have demonstrated high stability and scalability across different kinds of buildings - high-rise, shopping mall, and hospital. Such versatility allows them to be integrated into Building Information Modeling (BIM) systems and emergency response platforms. As a result, this paves the way for automatic generation of evacuation routes. This allows us to move from outdated "nearest exit" strategies to much more realistic and efficient approaches.

The scientific novelty of the research results lies in the first-time proposal of a capacity-aware objective function with nonlinear quadratic penalties for exit overloading, and in the development of modified swarm intelligence algorithms, specifically adapted for evacuation planning task. In particular, this study introduces two methods – Modified PSO (PSO_{MI}) and Enhanced ACO (ACO_{EH}). The main parameters were altered in a way that allows algorithms to take into account the throughput capacity of the exits. In particular, the higher inertia weight in PSO and the stronger heuristic information in ACO helped to stay away from the routes that have strict capacity constraints and, as a result, avoid receiving huge penalties.

Moreover, the study conducts a detailed comparative analysis of how these algorithmic modifications affect performance in highly constrained evacuation conditions. These results clearly reveal a trade-off between optimality and reliability: PSO_{MI} achieves the lowest average evacuation cost, which means that its overall solution is more optimal, whereas ACO_{EH} works better with congested exits and complex architectural bottlenecks.

The practical significance of the research results is that it can be directly applied to the evacuation planning process and the tools used for it. This helps to make important decisions faster in large, complex buildings with high population density. Instead of simply sending everyone to the nearest exit, our approach also considers how many people each exit can accommodate, which in turn helps to find more practical and realistic routes. Through such a scheme, we can significantly reduce the overall evacuation time and increase the safety of the process in real emergencies. These findings can be incorporated into Intelligent Building Management systems and emergency response protocols, contributing to the creation of more reliable and optimized evacuation strategies.

CONCLUSIONS

The research demonstrated that modified swarm intelligence algorithms can be efficiently applied for evacuation planning under severe capacity constraints. For this purpose, a new objective function was developed that includes severe penalties for congestion and crowding. As a result, the algorithms are aimed at finding the most optimal route while simultaneously trying to perform a more even distribution of population flows.

The results confirmed that Modified PSO (PSO_{MI}) and Enhanced ACO (ACO_{EH}) are suitable for solving such a task. Due to practical parameter changes, in particular, better "exploratory" behavior in PSO and stronger heuristics in ACO, these algorithms work more efficiently in a complex search space. In contrast to the basic shortest path method, which often leads to extreme congestion at exits, both modified approaches consistently demonstrated better results in all considered scenarios, including high-rise building, shopping mall and hospital. In some cases, the overall evacuation delays were reduced to 55 %. This strongly emphasizes the main idea of the study: efficient evacuation strategy depends on both: finding the shortest route and the correct distribution of population flows, while taking into account the throughput capacity of the exits.

Another important insight is the trade-off between the two approaches. PSO_{MI} provides a better overall result and runs very fast, so it is perfect for situations where immediate recalculation of routes is required. ACO_{EH} is more stable and predictable, i.e. it produces fewer "jumps" in the results, which is especially important in critical environments where reliability is of utmost importance.

The outcomes of this study can help urban planners and facilities managers make reasoned decisions. The PSO_{MI} algorithm would be an excellent component of intelligent building management systems and adaptive real-time evacuation guidance tools, since the need for quick re-optimization is critical there. On the other hand, the consistency of ACO_{EH} makes it a reliable choice for long-term evacuation planning in mission-critical facilities.

Future work shall primarily consider improving the presented model by allowing it to reflect

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dynamic changes in capacity that may arise from route blockages or speed fluctuations. Additionally, future research aims to expand the experimental comparison by adapting other popular population-based metaheuristics – specifically genetic algorithms (GA) and Grey Wolf Optimization (GWO) – to evaluate their performance under conditions of non-linear bandwidth penalization. Besides, stochastic models of human behavior, such as panic or crowding, may be integrated into new studies. Also, research on multi-objective optimization techniques should be conducted to find the optimal balance between factors such as evacuation time, travel distance and the needs of vulnerable populations. Such improvements will not only increase the accuracy of the evacuation-planning model, but also expand its scope for planning even the most modern and complex infrastructures.

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Financing: Research was carried out without financial support

Accessibility data: The simulation code, used to obtain given results, can be made available on a request.

Using artificial intelligence tools: During preparation manuscript used tool Claude Sonnet 5 (Medium) of artificial intelligence (AI) for grammatical and stylistic text checks. All fragments processed by him were checked and edited by the author. AI was not used to generate text, formulas, and tables, formation scientific provisions, receipt results or formulation conclusions. Scientific the provisions, results and conclusions are my own, intellectual by the contribution of the authors

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Ройовий інтелект у міському середовищі: планування евакуації в умовах надзвичайних ситуацій

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АНОТАЦІЯ

Актуальність дослідження визначається тим, що в умовах сучасної урбанізації безпека великих громадських об'єктів дедалі більше залежить від здатності систем управління оперативно й рівномірно розподіляти людські потоки під час надзвичайних ситуацій. Класичні алгоритми, орієнтовані лише на найкоротший шлях, ігнорують обмежену пропускну здатність виходів, провокуючи затори, що критично збільшує час евакуації. Об'єктом дослідження є процес екстреної евакуації у великих будівлях з кількома виходами, змодельований як задача мережевого потоку з обмеженою пропускною здатністю. **Метою** статті є розробка та валідація моделі ройового інтелекту, яка дозволяє ефективно розподіляти потоки людей між виходами з урахуванням їхньої пропускної здатності та зменшенням загального часу евакуації. Для досягнення цієї мети було вирішено такі **завдання**: побудовано нелінійну цільову функцію зі штрафами за утворення заторів; адаптовано параметри ройових алгоритмів для пошуку в перевантажених мережах; проведено емпіричну оцінку сценаріїв евакуації та визначено компроміс між обчислювальною швидкодією та стабільністю рішень. У роботі використано такі **методи**: методи теорії графів для опису структури будівель; апарат математичного програмування для побудови нелінійної цільової функції; та методи ройового інтелекту для пошуку глобального оптимуму в багатовимірному просторі рішень. **Наукова новизна** полягає у тому, що запропоновано нову цільову функцію, яка включає сильні нелінійні, квадратичні штрафи за перевантаження та порушення пропускної здатності виходів. Для ефективної оптимізації цього середовища з високими штрафами у стандартних алгоритмах оптимізації рою частинок та оптимізації колоній мурах були змінені основні параметри, що призвело до появи варіантів Modified Particle Swarm Optimization та Enhanced Ant Colony Optimization. **Результати** моделювання для різних типів споруд підтвердили, що запропоновані підходи зменшують кумулятивні затримки евакуації до п'ятдесяти п'яти відсотків порівняно з класичними методами пошуку найкоротшого шляху. **Практичне значення** одержаних результатів полягає у доповненні існуючих інженерних методів планування евакуації, що базуються на принципі найкоротшого шляху, механізмом балансування навантаження між виходами з урахуванням їхньої пропускної здатності. Це усуває проблему утворення локальних заторів і перевантаження окремих виходів в умовах масової евакуації, а також забезпечує алгоритмічну основу для інтеграції розроблених моделей у BIM-системи з метою автоматичної генерації безпечних маршрутів у режимі реального часу. **Висновки**. Проведений аналіз доводить, що запропонована модель ройового інтелекту ефективно розподіляє потоки людей між виходами з урахуванням їхньої пропускної здатності та суттєво зменшує кумулятивні затримки евакуації порівняно з базовим методом найкоротшого шляху, що підтверджує валідність розробленого підходу для практичного планування евакуації.

Ключові слова: екстрена евакуація; ройовий інтелект; пропускна здатність виходів; динаміка натовпу; оптимізація маршрутів;, безпека будівель; оптимізація рою частинок; алгоритм мурашиної колонії; балансування навантаження; математичне моделювання

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