3D Geodata Based Optimization of UAV Docking Stations in Mountainous Areas for Emergency Response

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Abstract

In recent years, the increasing frequency of natural disasters in remote and rugged areas has underscored the importance of unmanned aerial vehicles (UAVs) for rapid emergency response. This paper presents a novel approach for optimizing the placement of UAV docking stations in mountainous terrain for emergency operations. We develop a comprehensive, 3D Geodata framework that integrates 3D Digital Elevation Models (3D DEM), building infrastructure, and road network data to create a realistic three-dimensional optimization environment. The proposed system employs an Enhanced Adaptive Particle Swarm Optimization (EAPSO) algorithm with adaptive parameters, diversity maintenance mechanisms, and intelligent convergence detection to effectively handle the complex constraints of mountainous environments. Experimental results demonstrate that our 3D-aware EAPSO approach achieves superior performance in balancing coverage efficiency, energy consumption, and network connectivity compared to conventional optimization methods. The proposed system provides a scientific foundation for improving emergency response capabilities in challenging geographical environments.

1. Introduction

With the emergence of natural disasters in remote and rugged areas, deploying UAVs for rapid emergency response has become a vital component of contemporary disaster management (Ghazzai et al., 2017; Lucic et al., 2023). Unlike urban or flat environments, mountainous regions pose formidable obstacles — steep slopes, narrow valleys, and unpredictable weather—that severely constrain ground access and signal propagation (Adam et al., 2021). Strategic placement of UAV nest sites, where drones can recharge and receive task assignments, is therefore essential to minimize response times and maximize operational coverage under such harsh conditions (Brahim et al., 2017 ;Ghazzai et al., 2019).

In recent years, various optimization frameworks have been proposed for UAV docking station placement in different application scenarios. For disaster response and emergency operations, some studies integrate Voronoi-based partitioning with connectivity constraints to reduce average service distance in both LoS and NLoS conditions (e.g., Huang & Savkin, 2022). Related work on UAV deployment has also explored optimal altitude selection and 3D placement strategies for maximizing coverage and energy efficiency (Al-Hourani et al., 2014; Alzenad et al., 2017; Alzenad et al., 2018; Bor-Yaliniz et al., 2016). Others—particularly in vehicular ad-hoc networks (VANETs)—leverage Particle Swarm Optimization (PSO) combined with vehicle density and historical coverage data to determine dynamic UAV deployment positions, using task scheduling to further reduce service time waste (Islam et al., 2022; Adam et al., 2021). In intelligent transportation systems (ITS), penalty-weighted k-means clustering and PSO have been used to select docking station locations and build multi-UAV scheduling models that balance coverage and battery life (Ghazzai et al., 2019). Lucic et al. (2020) extend these ideas by proposing a generalized dynamic planning framework for green UAV-assisted ITS infrastructure, while Lucic et al. (2023) provide an overview of smart aerial infrastructure for ITS and smart cities. For three-dimensional multi-UAV base deployment, non-convex optimization models with purpose-designed heuristic algorithms convert user QoS requirements into concentric coverage constraints, achieving superior computational efficiency compared to linear approximations (Adam et al., 2021). Circle-packing theory has also been applied to analyze coverage probability, flight height, and antenna gain, proposing altitude-and-beamwidth adjustments to reduce interference (Mozaffari et al., 2016). More broadly, UAV communication networks and routing architectures have been studied from civil, networking, and IoT perspectives, while UAV platforms have also shown value in emergency search-and-rescue scenarios and in docking or landing platform development (Gupta et al., 2016; Hayat et al., 2016; Zhang et al., 2019; Molina et al., 2012; Grlj et al., 2022).

The metaheuristic optimization algorithms have been increasingly adopted for facility location and deployment problems. Among them, Particle Swarm Optimization (PSO) has attracted significant attention due to its simple structure, fast convergence, and relatively few control parameters. PSO simulates cooperative swarm search, where particles iteratively update positions by sharing information about the best solutions found. Compared with genetic algorithms or ant colony optimization, PSO demonstrates higher computational efficiency and better scalability in continuous, high-dimensional search spaces. These advantages make it effective for complex spatial optimization problems, such as determining optimal locations for network nodes or service facilities in two- or three-dimensional areas. For example, PSO has been applied to optimize UAV 3D placement to minimize transmit power for indoor coverage (Shakhatreh et al., 2017) and to solve the Maximal Covering Location Problem for emergency ambulance deployment with high coverage rates (Lutfi et al., 2013).

Similarly, PSO-based methods have been used to maximize coverage in wireless sensor networks (Siamantas & Kandris, 2024) and to optimize UAV placement as aerial fog nodes, reducing drone numbers while ensuring coverage (Tang et al., 2020). In addition, PSO has been systematically reviewed as a broadly applicable optimization framework, further supporting its suitability for deployment and siting problems (Gad, 2022). These successes support its suitability for UAV docking station siting.

Despite these advances, existing work often overlooks two key issues. First, most algorithms assume flat or moderately varying terrain, neglecting three-dimensional elevation constraints that are crucial in mountainous regions. Second, few studies account for the availability of existing power facilities when selecting candidate sites, which can lead to sharply increased construction and operational costs. Consequently, there remains a lack of comprehensive models tailored specifically for UAV nest site selection in rugged, power-constrained environments.

Therefore, in this study, we develop a data - driven optimization model and an enhanced Adaptive PSO algorithm to address those gaps. By integrating high- resolution Digital Elevation Models (DEM), building data, and road network data, our approach explicitly incorporates three- dimensional terrain constraints and considers existing power facility availability—providing a scientific foundation for improving disaster preparedness and emergency response in challenging mountainous settings..

2. Methodology

In order to address the challenge of UAV nest-site placement in mountainous emergency-response scenarios, our methodology combines comprehensive terrain and infrastructure data with a suite of advanced multi-objective optimization techniques. We first construct a realistic three-dimensional model of the study area, then define and calibrate our performance metrics and constraints, and finally evaluate and compare five distinct algorithms to identify the most effective deployment strategies under varying operational requirements(Ghazzai et al., 2019).

2.1 Data Integration and Modeling

This research develops a sophisticated multi-objective optimization model for UAV docking station selection that integrates diverse geographical and operational data sources. The model incorporates real-world geographical data including Digital Elevation Models (DEM), building infrastructure, and road network information to create a realistic three-dimensional optimization environment. The study area is situated in the mountainous region of Guangzhou and includes 8,543 candidate building locations, all of which are restricted to existing building rooftops to ensure that no new electrical infrastructure is required for establishing UAV-nest sites. In addition, 100 task points are randomly generated across the road network to represent potential emergency-response targets and to capture the inherently stochastic nature of emergency incident occurrences.This extensive dataset ensures that the optimization results reflect real-world deployment scenarios and constraints.

2.2 Problem Formulation

The model is formulated to simultaneously optimize three critical performance metrics: coverage efficiency, energy consumption, and network connectivity (Islam et al., 2022). Coverage efficiency measures the percentage of emergency response targets that can be effectively served by the deployed UAV docking stations within specified response time constraints, typically ranging from 5 to 15 minutes depending on mission criticality (Savkin et al., 2022). Energy consumption optimization ensures sustainable operations by minimizing flight distances and energy requirements while maintaining adequate service levels, considering factors such as battery capacity, flight speed, and payload weight. Network connectivity optimization addresses line-of-sight communication requirements essential for coordinated emergency response operations, ensuring reliable data transmission and command control capabilities.

The UAV docking station placement problem in mountainous terrain can be formulated as a constrained multi-objective optimization problem. Given a set of candidate locations

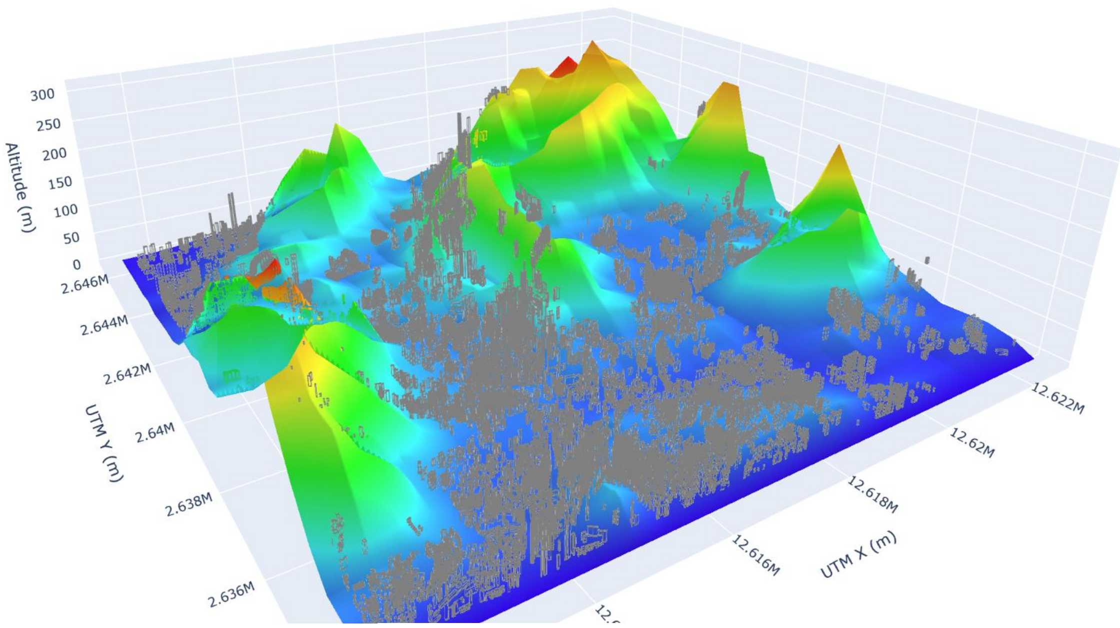

Figure 1 3D modeling with multi-data fusion (building rooftops) and emergency response task points, the objective is to determine the optimal placement of a fixed number of docking stations to maximize coverage while satisfying energy and line-of-sight constraints.

Formally, let B represent the set of candidate building locations, where each b_i denotes the 3D coordinates of a potential docking station. Let T be the set of task points representing potential emergency locations, where each t_j denotes the 2D coordinates of a task point. The objective is to select a subset of size K (where K is the number of docking stations to be deployed) that optimizes the following objectives. A summary of the main symbols is provided in Appendix A.

2.2.1 Coverage Efficiency

Maximize the percentage of task points covered by at least one docking station:

$$\text{Coverage}(S) = \frac{|t_j \in T : \min_{b_i \in B} d(t_j, b_i) \le R|}{|T|} \times 100\% \quad (2.1)$$

where $d(t_j, b_i)$ is the Euclidean distance between task point t_j and docking station b_i, and $R = 5000m$ is the UAV coverage radius.

2.2.2 Energy Consumption Penalty

Consider the energy constraints of UAV operations, the energy consumption for each flight is calculated as:

$$d_{\text{flight}}(t_j, b_i) = \sqrt{d^2_{\text{horizontal}}(t_j, b_i) + h^2_{\text{deployment}}}$$

$$t_{\text{flight}}(t_j, b_i) = \frac{d_{\text{flight}}(t_j, b_i)}{v_{\text{UAV}}}$$

$$E(t_j, b_i) = P_m \times t_{\text{flight}}(t_j, b_i) \quad (2.2)$$

where $h_{\text{deployment}} = 60m$ is the UAV deployment altitude, $v_{\text{UAV}} = 18m/s$ is the flight speed, and $P_m = 10W$ is the motion power consumption.

The energy penalty function is defined as:

$$\text{Energy Penalty}(S) = \sum_{t_j \in T_{\text{covered}}} \max(E(t_j, \text{nearest}(t_j, S)) - E_{\max}, 0) \times \alpha \quad (2.3)$$

where $E_{\max} = 400{,}000J$ is the battery capacity, $\alpha = 0.001$ is the energy penalty factor, and T_{covered} is the set of covered task points.

2.2.3 Line-of-Sight Connectivity Penalty

In mountainous terrain, line-of-sight connectivity between docking stations is critical for communication. The LOS penalty is calculated using a non-linear function:

$$LOSPenalty(S) = \begin{cases} 200, & if N_{broken} = 1 \\ 500, & if\, 2 \le N_{broken} \le 3 \\ 100 \times N^2_{broken}, & if N_{broken} > 3 \end{cases} \quad (2.4)$$

where N_{broken} is the number of broken line-of-sight connections between docking stations. The line-of-sight check is performed by step-wise sampling along the connecting line:

$$\text{LOS}(b_i, b_j) = \forall k \in [0, \text{steps}] : z_{\text{line}}(k) > z_{\text{terrain}}(x_k, y_k) + 10m \quad (2.5)$$

2.2.4 Comprehensive Fitness Function

The overall fitness function to be maximized：

$$\text{Fitness}(S) = \text{Coverage}(S) - \text{Energy Penalty}(S) - \text{LOS Penalty}(S) \quad (2.6)$$

The above function subjects to the following constraints:

1. The number of selected docking stations is exactly K.
2. Each docking station must be placed on a valid building rooftop.
3. The altitude of each docking station must be above the minimum safe altitude.

2.3 Enhanced Adaptive Particle Swarm Optimization Algorithm

To effectively solve the complex optimization problem of UAV docking station placement in mountainous terrain, we propose an Enhanced Adaptive Particle Swarm Optimization (EAPSO) algorithm with several novel improvements specifically designed for this application domain.

Mountainous terrain presents unique challenges for UAV docking station deployment that traditional optimization algorithms struggle to address effectively. The complex topography creates highly irregular search spaces with numerous local optima, while terrain-induced communication shadows and variable elevation profiles demand sophisticated adaptive mechanisms. Our EAPSO algorithm incorporates several mountainous terrain–specific enhancements to overcome these challenges and achieve superior optimization performance in such complex environments.

2.3.1 Non-linear Inertia Weight Adaptation

Mountainous terrain optimization requires a careful balance between global exploration and local exploitation due to the presence of multiple elevation-induced local optima and terrain-constrained feasible regions. Traditional linear inertia weight decay often leads to premature convergence in valley regions or insufficient exploration of elevated terrain features. To address this challenge, we implement an exponential decay function for the inertia weight that provides better balance between exploration and exploitation throughout the optimization process:

$$w(t) = w_{\max} \cdot \left(\frac{w_{\min}}{w_{\max}}\right)^{\frac{t}{T_{\max}}} \quad (2.7)$$

where $w(t)$ is the inertia weight at iteration t, $w_{\max} = 0.95$ and $w_{\min} = 0.3$ are the maximum and minimum inertia weights, and $T_{\max} = 150$ is the maximum number of iterations. The selection of the two inertia weight parameters, together with this non-linear decay mechanism, enables more aggressive global exploration during the early iterations to identify critical ridge and peak locations within the terrain, while providing more focused local exploitation in later iterations to fine-tune UAV docking station positions within terrain-constrained feasible regions. The exponential nature of this decay is particularly well-suited for mountainous environments, where the complexity of the search space varies significantly with elevation and terrain features.

2.3.2 Diversity-based Adaptive Parameters

Mountainous terrain creates natural clustering of feasible solutions around elevated building locations and ridge lines, leading to population convergence issues that traditional PSO algorithms cannot effectively handle. The complex three-dimensional nature of mountainous search spaces requires dynamic parameter adjustment based on population diversity to maintain effective exploration of terrain features. The population diversity is calculated as the normalized average Euclidean distance between all pairs of particles:

$$D(t) = \frac{\sum_{i=1}^{N_p} \sum_{j=i+1}^{N_p} || X_i(t) - X_j(t) ||}{\binom{N_p}{2} \cdot S_{\text{space}}} \tag{2.8}$$

where $N_p = 40$ is the number of particles, $X_i(t)$ is the position of particle i at iteration t, and S_{space} is a normalization factor based on the search space size.

The cognitive and social learning factors are dynamically adjusted based on the current population diversity:

$$c_1(t) = c_{1,\text{base}}(t) \times f_{\text{diversity}}(D(t)) \tag{2.9}$$

$$c_2(t) = c_{2,\text{base}}(t) \times g_{\text{diversity}}(D(t)) \tag{2.10}$$

where the base values are determined by linear interpolation:

$$c_{1,\text{base}}(t) = c_{1,\text{initial}} - (c_{1,\text{initial}} - c_{1,\text{final}}) \times \frac{t}{T_{\max}} \tag{2.11}$$

$$c_{2,\text{base}}(t) = c_{2,\text{initial}} + (c_{2,\text{final}} - c_{2,\text{initial}}) \times \frac{t}{T_{\max}} \tag{2.12}$$

with parameters $c_{1,\text{initial}} = 2.0$, $c_{1,\text{final}} = 0.8$, $c_{2,\text{initial}} = 0.8$, and $c_{2,\text{final}} = 2.2$.

The diversity adjustment functions are specifically designed to handle mountainous terrain convergence patterns:

Algorithm EAPSO for Docking Station Placement

Initialize B particles with random positions for S docking stations
Project positions to valid building candidates
Initialize velocities, personal best (pbest), and global best (gbest)
t = 0
while Not converged **do**
  Update adaptive parameters w(t), c_1(t), c_2(t)
  for each particle b = 1, 2, ..., B do
    Evaluate fitness: coverage ratio - energy penalty - LoS penalty
    Update pbest_b if current fitness is better
  end for
  Update gbest from all pbest positions
  for each particle b = 1, 2, ..., B do
    Update velocity: v_b(t+1) = w(t)·v_b(t) + c_1(t)·r_1·(pbest_b - x_b(t)) + c_2(t)·r_2·(gbest - x_b(t))
    Update position: x_b(t+1) = x_b(t) + v_b(t+1)
    Project x_b(t+1) to nearest building candidate
  end for
  if diversity < threshold then
    Apply mutation to worst particles
  end if
  t = t + 1
end while
Return gbest as optimal docking station positions

$$f_{diversity}(D) = \begin{cases} 1.0 + 0.15(D_{min} - D), & \text{if } D < D_{min} \\ 1.0 - 0.05(D - 0.4), & \text{if } D > 0.4 \\ 1.0, & \text{otherwise} \end{cases} \tag{2.13}$$

$$g_{diversity}(D) = \begin{cases} 1.0 - 0.05(D_{min} - D), & \text{if } D < D_{min} \\ 1.0 + 0.1(D - 0.4), & \text{if } D > 0.4 \\ 1.0, & \text{otherwise} \end{cases} \tag{2.14}$$

where $D_{\min} = 0.1$ is the minimum diversity threshold. These functions enhance cognitive learning when particles cluster around terrain features (low diversity) and boost social learning when particles are well-distributed across the mountainous landscape (high diversity), ensuring effective exploration of both local terrain features and global mountain ranges.

2.3.3 Selection of Key Parameters

We employ a swarm of 40 particles and a 150-iteration budget, together with a decreasing inertia weight (from 0.95 to 0.3) and a schedule of decreasing cognitive and increasing social learning factors (c_1 : 2.0 → 0.8; c_2 : 0.8 → 2.2). Sensitivity analysis indicates that this configuration attains near-optimal average fitness within the 150-iteration budget while exhibiting low dispersion and enhanced feasibility stability, thereby yielding a favorable trade-off between solution quality and computational cost. Although larger swarms and longer iteration counts can further improve fitness, they incur substantially higher computational overhead; conversely, smaller swarms converge faster but are more susceptible to premature convergence. Hence, the chosen configuration strikes an effective balance between rapid convergence and robustness to constraints, making it well suited to the scenario assumed in this study.

2.3.4 Intelligent Convergence Detection and Mutation

Mountainous terrain optimization is particularly susceptible to stagnation in local optima created by terrain features such as valleys, ridges, and isolated peaks. Traditional convergence detection methods often fail to distinguish between true global convergence and terrain-induced local stagnation. Our algorithm incorporates an intelligent convergence detection mechanism specifically designed for mountainous environments:

$$\text{Stagnation}(t) = \begin{cases} \text{Stagnation}(t-1) + 1, & \text{if } \left| f_{gbest}(t) - f_{gbest}(t-1) \right| < \epsilon \\ 0, & \text{otherwise} \end{cases} \tag{2.15}$$

where $f_{\text{gbest}}(t)$ is the global best fitness at iteration t, and $\epsilon = 10^{-4}$ is the convergence threshold.

When stagnation is detected ($\text{Stagnation}(t) \geq 15$), a diversity-enhancing mutation operation is applied with probability:

$$P_{\text{mutation}}(t) = \begin{cases} 2 \times P_{\text{base}}, & \text{if } D(t) < D_{\min} \\ P_{\text{base}}, & \text{otherwise} \end{cases} \tag{2.16}$$

where $P_{\text{base}} = 0.15$ is the base mutation rate. This mutation mechanism is crucial for escaping terrain-constrained local optima and exploring alternative mountain regions that may contain superior docking station configurations. The adaptive mutation probability ensures more aggressive diversification when particles are trapped in narrow terrain features.

2.3.5 Position and Velocity Update

The core PSO update equations are enhanced to handle the three-dimensional nature of mountainous terrain optimization:

$$v_{i,d}^{t+1} = w(t) \cdot v_{i,d}^{t} + c_1(t) \cdot r_1 \cdot (p_{i,d}^{t} - x_{i,d}^{t}) + c_2(t) \cdot r_2 \cdot (g_d^{t} - x_{i,d}^{t}) \tag{2.17}$$

$$x_{i,d}^{t+1} = x_{i,d}^{t} + v_{i,d}^{t+1} \tag{2.18}$$

where $r_1, r_2 \sim U(0,1)$ are random factors, and velocity is limited to $|v_{i,d}^{t+1}| \leq 1000m$ to prevent excessive jumps across terrain features that could violate geographical constraints.

2.3.6 Candidate Point Projection

Mountainous terrain imposes strict geographical constraints on feasible docking station locations, as stations must be placed on actual building rooftops rather than arbitrary coordinates. To ensure all solutions remain feasible throughout the optimization process, a KD-tree–based nearest neighbor projection is applied:

$$X_{i,j}^{\text{projected}}(t) = \arg\min_{b_k \in B} \| X_{i,j}(t) - b_k \|_2 \tag{2.19}$$

This projection mechanism is essential for mountainous terrain optimization because it ensures that all particle positions correspond to realistic deployment locations while maintaining the optimization algorithm's ability to explore the three-dimensional search space effectively. The KD-tree structure provides efficient nearest neighbor queries even with thousands of candidate building locations distributed across complex mountainous topography.

3. Evaluation

3.1 Experimental Setup

The experiments were conducted using a high-resolution 3D Digital Elevation Model with 10-meter spatial resolution, the used building footprint data contains 8,543 structures, and road network data comprising major and minor roads in the study area. From the road network, we generated 100 task points representing potential emergency locations using stratified random sampling to ensure coverage of different road types and geographical areas.

All experiments were conducted in Python 3.13 on Windows 11. The proposed EAPSO algorithm was implemented with NumPy for vectorized particle updates and random sampling, SciPy (ndimage/map_coordinates) for terrain-aware sampling and interpolation, and scikit-learn's KDTree for efficient nearest-neighbor snapping of particle positions to rooftop candidate locations. Progress scheduling and monitoring were handled with tqdm. Geospatial data handling (outside the optimization core) used Rasterio for DEM I/O, GeoPandas and Shapely for vector processing, and PyProj for coordinate transforms; Plotly was used only for visualization and is orthogonal to the optimization routine.

As Figure 2 shows, we compare the performance of different algorithms in terms of average and standard-deviation of computational times. The considered algorithms are listed below.

• K-means clustering: We adopt K-means as the algorithmic baseline due to its wide applicability, low computational cost, and the interpretability and reproducibility of its results. This baseline approach groups task points into clusters and places docking stations at the centroids of these clusters, with each centroid subsequently projected onto the nearest feasible building location.
• Genetic Algorithm (GA): A population-based evolutionary algorithm with custom crossover and mutation operators designed for the docking station placement problem.
• Non-dominated Sorting Genetic Algorithm II (NSGA-II): A multi-objective evolutionary algorithm that explicitly handles

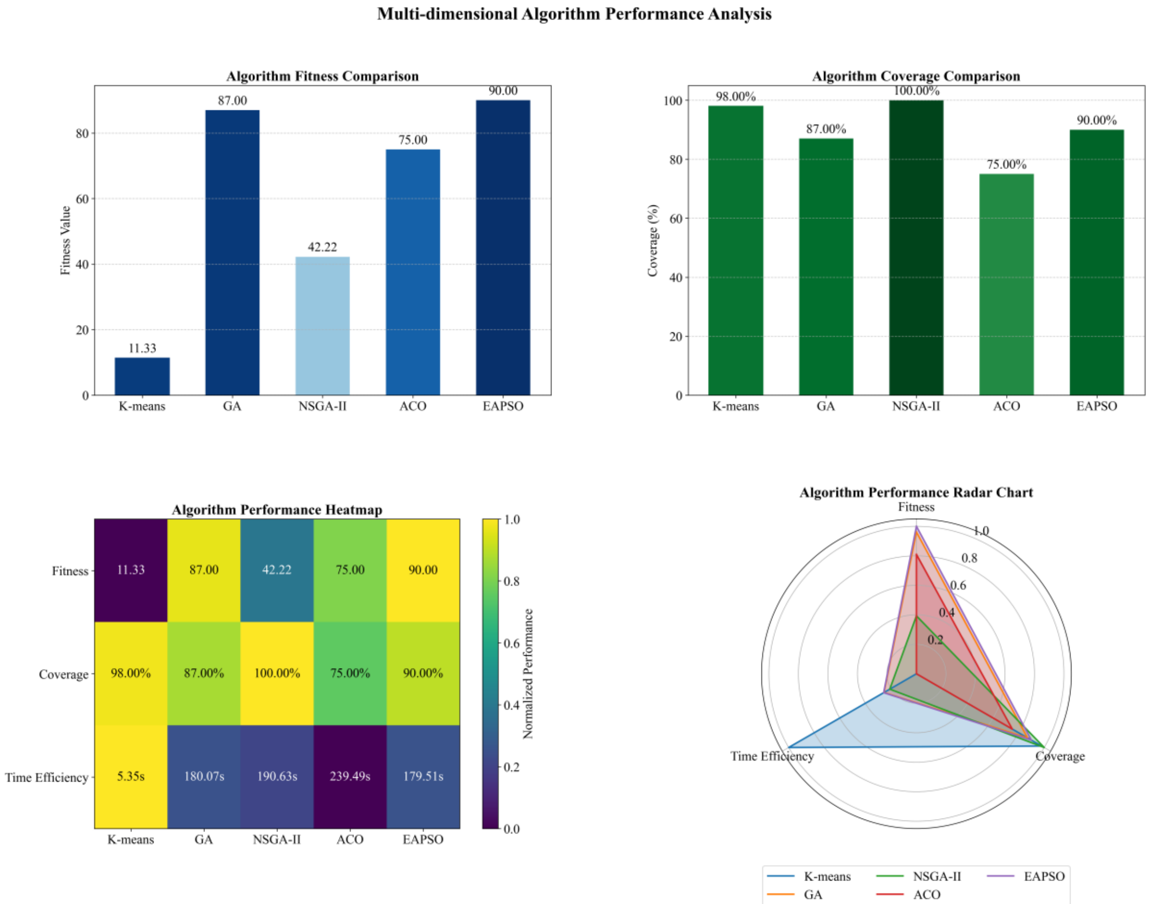

Figure 2 Multi-Dimensional Comparative Analysis of Algorithm Performance

the trade-offs between coverage, energy consumption, and line-of-sight connectivity.
• Ant Colony Optimization (ACO): A swarm intelligence approach that uses pheromone-based search to find optimal docking station configurations.
• Enhanced Adaptive Particle Swarm Optimization (EAPSO): Our proposed PSO algorithm with adaptive parameters, diversity maintenance, and intelligent convergence detection.

The implementation details and code are available in our GitHub repository.[1]

3.2 Evaluation Metrics

We evaluated the algorithms using the following metrics:
1. Coverage Efficiency: The percentage of task points covered by at least one docking station within the UAV's operational range.
2. Fitness Score: The overall quality of the solution, incorporating coverage, energy consumption, and line-of-sight connectivity.
3. Computational Time: The time required to find the best solution, measured in seconds.

4. Simulation Results

The experimental evaluation demonstrates the superior performance of the proposed adaptive PSO algorithm in mountainous UAV docking station site selection compared to conventional optimization approaches. The comparative analysis includes K-means clustering, Genetic Algorithm (GA), NSGA-II multi-objective optimization, and Ant Colony Optimization (ACO).

4.1 Algorithm Performance Analysis

The comparative evaluation indicates that EAPSO delivers superior overall performance under mountainous deployment constraints. EAPSO attains the highest fitness score of 90.00, surpassing GA (87.00), ACO (75.00), NSGA-II (42.22), and K-means (11.33). In terms of coverage, NSGA-II and K-means achieve 100.00% and 98.00% task-point coverage respectively, while EAPSO reaches 90.00%, GA 87.00%, and ACO 75.00%. Regarding computational cost, EAPSO completes in 179.51s, comparable to GA (180.07s), faster than NSGA-II (190.63s), and markedly faster than ACO (239.49s), while still delivering the highest fitness.

Crucially, high coverage does not necessarily yield high fitness because the evaluation integrates feasibility penalties. Solutions are penalized when servicing task points requires energy beyond the battery capacity or when docking stations lack line-of-sight connectivity due to terrain occlusions. As a result, placements that push stations closer to task clusters may inflate coverage but simultaneously incur substantial energy and LoS penalties, reducing the overall fitness. This behavior is consistent with the operational requirements of emergency UAV siting in mountainous regions, where feasibility, safety, and reliable communication are as critical as spatial coverage.

Overall, EAPSO achieves the most favorable trade-off between

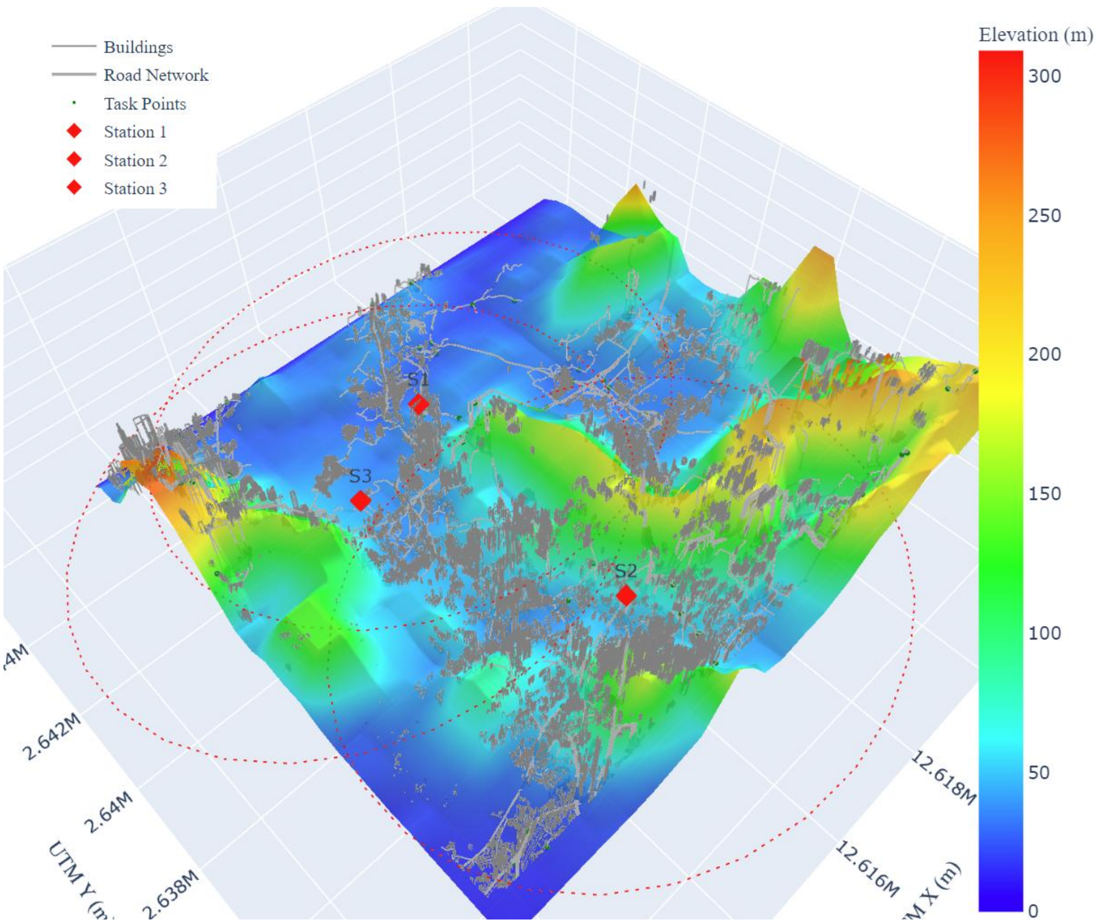

Figure 3 3D UAV Docking Stations Distribution

[1] GitHub repository: https://github.com/tgis-lab/site-selection-for-uav

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coverage, energy feasibility, and line-of-sight compliance. Its high fitness (90.00) together with competitive runtime and adequate coverage (90.00%) demonstrates robust optimization under complex topographic constraints, making EAPSO the preferred approach for emergency UAV docking station placement in mountainous environments.

4.2 Constraint Satisfaction Performance

The adaptive PSO algorithm demonstrates superior constraint handling capabilities in mountainous terrain scenarios. The line-of-sight constraint satisfaction rate significantly exceeds other algorithms, with minimal communication obstruction between selected docking stations. This achievement stems from the algorithm's sophisticated terrain-aware fitness evaluation and graduated penalty mechanisms.

Energy consumption analysis reveals efficient UAV deployment strategies, with the EAPSO maintaining energy requirements within battery capacity limits for 90% of covered task points. The algorithm's three-dimensional flight path optimization considers both horizontal distances and vertical deployment requirements, ensuring practical feasibility in mountainous emergency response scenarios.

4.3 Computational Efficiency Analysis

The comprehensive performance heatmap illustrates the EAPSO algorithm's balanced optimization across multiple criteria(Figutre 2). The algorithm achieves high normalized scores in fitness, coverage, and computational efficiency, demonstrating robust performance across diverse evaluation metrics. The radar chart visualization confirms PSO's superior multi-dimensional performance profile compared to conventional approaches.

Execution time analysis shows competitive computational efficiency, with the adaptive PSO completing optimization within reasonable time constraints suitable for emergency response planning applications. The algorithm's convergence *characteristics demonstrate stable performance with effective diversity maintenance throughout the optimization process.*

4.4 Three-Dimensional Analysis

The experimental validation demonstrates the EAPSO algorithm's superior performance in complex mountainous terrain, as evidenced by the comprehensive 3D visualization results shown in the terrain analysis. The algorithm successfully identifies optimal docking station configurations across challenging topographical features, including steep elevation gradients ranging from 50m to 300m and complex ridgeline formations that characterize the study area.

As Figure 3 shows, the EAPSO algorithm effectively navigates the intricate landscape topology, strategically positioning docking stations to maximize coverage while maintaining critical line-of-sight communication links. The algorithm's deployment strategy demonstrates remarkable adaptability to the terrain's natural constraints, with stations positioned at elevations that balance accessibility requirements with communication effectiveness. The spatial distribution pattern clearly shows how the algorithm leverages elevated positions along ridgelines and strategic valley locations to optimize the coverage network.

The graduated penalty mechanism proves instrumental in achieving this sophisticated terrain adaptation. Unlike conventional optimization approaches that often fail to satisfy geometric constraints in complex topography, the EAPSO maintains solution feasibility while achieving superior performance metrics. The visualization reveals how the algorithm successfully avoids placement in topographically unsuitable locations while ensuring comprehensive coverage of the target area, as indicated by the strategic positioning relative to the road network infrastructure.

The three-dimensional analysis confirms the algorithm's ability to balance competing objectives—coverage maximization, energy efficiency, and terrain constraint satisfaction—in real-world mountainous scenarios. This terrain-adaptive capability represents a significant advancement over traditional UAV deployment methodologies that fail to account for complex topographical realities.

5. Conclusion and Future Work

This paper presented a comprehensive approach to optimizing UAV docking station placement in mountainous terrain for emergency response operations. We developed a data-driven framework that integrates multiple geographical data sources and proposed an enhanced Adaptive Particle Swarm Optimization algorithm specifically designed to handle the complex constraints of mountainous environments. Our experimental results demonstrate that the proposed approach effectively balances coverage efficiency, energy consumption, and network connectivity, outperforming conventional optimization methods in this challenging application domain.

The analysis reveals that docking station selection should be tailored to specific emergency response scenarios and operational requirements. For comprehensive coverage optimization in well-planned deployment scenarios, NSGA-II provides optimal performance but at high computational cost. For multi-objective decision-making scenarios requiring detailed trade-off analysis, ACO offers superior flexibility and balanced performance. Our Adaptive PSO algorithm is particularly suitable for medium-scale emergency response operations where reliable performance and moderate computational requirements are essential, such as search and rescue missions in moderately complex terrain where consistent coverage is more important than absolute optimization.

Future work will focus on several promising directions. First, we plan to incorporate dynamic weather conditions and temporal variations in emergency response priorities into the optimization model, enhancing its robustness and adaptability to changing operational environments. Second, we will explore the integration of machine learning techniques to predict optimal docking station configurations based on terrain features and task distributions, potentially reducing computational requirements for large-scale deployment scenarios. Finally, we aim to extend the model to include heterogeneous UAV fleets with different operational capabilities and constraints, further enhancing the flexibility and effectiveness of emergency response systems in mountainous regions. By addressing these research directions, we hope to further advance the state-of-the-art in UAV deployment optimization for emergency response in challenging geographical environments, ultimately contributing to more effective disaster management and humanitarian assistance operations worldwide.

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Appendix A

Symbol	Definition
B	Set of candidate building locations
T	Set of emergency task points
K	Number of deployed UAV docking stations
$d(t_j, b_i)$	Distance between task point (t_i) and station (b_j)
R	UAV coverage radius
$E(t_j, b_i)$	Energy consumption for serving task point (t_i)
$E_{\max}$	UAV battery capacity
$w(t)$	Inertia weight at iteration (t)
$c_1(t)$, $c_2(t)$	Cognitive and social learning factors
$x_b(t)$, $v_b(t)$	Position and velocity of particle
g_{best}	Global best solution

Appendix A A summary of the main symbols used in this study