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Drone-Based Temporary Internet Network for Remote and Disaster Areas

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Abstract:

Reliable internet connectivity is vital for emergency communication and disaster management, yet many remote and rural regions remain without access to stable networks. This study presents a simulation-based framework for deploying Unmanned Aerial Vehicles (UAVs) to establish temporary internet connectivity in such regions. The proposed system employs a terrain-aware deterministic region-filling algorithm to determine optimal UAV placement, ensuring full coverage with minimal energy consumption and latency. UAVs act as aerial base stations operating within altitude and energy constraints, and the deployment is optimized to balance leftover energy among all drones. Simulation experiments are performed using MATLAB, NS-3, and OMNeT++ on the Pettimudi landslide region in Kerala, India. Results demonstrate that 100% coverage of a 4×4 km² disaster area can be achieved with only sixteen drones, maintaining network efficiency of 98% and latency below 200 ms. Comparative analysis with traditional planar UAV, satellite, and Cell-on-Wheels (COW) systems highlights superior scalability, energy efficiency, and deployment speed. The proposed model provides a reproducible and practical solution for rapid communication restoration in remote or disaster-affected regions.

Keywords: UAV, temporary internet, drone deployment, deterministic algorithm, coverage optimization, network simulation, energy efficiency.

شبكة إنترنت مؤقتة معتمدة على الطائرات المسيّرة للمناطق النائية والمتضررة من الكوارث

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مستخلص:

يُعد الاتصال الموثوق بالإنترنت أمرًا بالغ الأهمية للاتصالات الطارئة وإدارة الكوارث، ومع ذلك لا تزال العديد من المناطق الريفية والنائية تفتقر إلى الوصول إلى شبكات مستقرة. تقدم هذه الدراسة إطارًا مبنيًا على المحاكاة لنشر المركبات الجوية غير المأهولة (UAVs) بهدف إنشاء اتصال إنترنت مؤقت في مثل هذه المناطق. يعتمد النظام المقترح على خوارزمية تعبئة مناطق حتمية تعتمد على شكل التضاريس لتحديد أفضل مواقع لنشر الطائرات المسيّرة، مما يضمن تغطية كاملة مع تقليل استهلاك الطاقة وزمن الوصول. تعمل الطائرات المسيّرة كمنصات بث جوية ضمن قيود الارتفاع والطاقة، ويتم تحسين عملية النشر لتحقيق توازن في الطاقة المتبقية بين جميع الطائرات. تم إجراء التجارب باستخدام برامج MATLAB وNS-3 وOMNeT++ على منطقة الانهيار الأرضي في "بيتمودي" بولاية كيرالا في الهند. أظهرت النتائج إمكانية تحقيق تغطية بنسبة ١٠٠٪ لمنطقة كوارث بمساحة 4×4 كم² باستخدام ست عشرة طائرة فقط، مع الحفاظ على كفاءة شبكة تبلغ ٩٨٪ وزمن وصول أقل من ٢٠٠ مللي ثانية. كما يوضح التحليل المقارن مع أنظمة الطائرات المسيرة التقليدية، والأقمار الصناعية، وأنظمة الأبراج المتنقلة (COW) تفوق النموذج المقترح من حيث قابلية التوسع وكفاءة الطاقة وسرعة النشر. يوفر النموذج المقترح حلاً عمليًا وقابلاً للتطبيق لإعادة إنشاء الاتصالات بشكل سريع في المناطق النائية أو المتضررة من الكوارث.

1. Introduction

Reliable internet connectivity is indispensable for modern communication, information exchange, and disaster response; however, large portions of the world—particularly rural, remote, and disaster-prone regions—remain disconnected. According to recent ITU statistics, nearly 2.9 billion individuals globally still lack consistent internet access, limiting their ability to participate in critical activities such as emergency coordination, telemedicine, online learning, and post-disaster management. Conventional communication infrastructures, including fiber-optic networks and cellular towers, are often unavailable or severely damaged in these environments, underscoring the necessity for rapid, flexible, and cost-effective solutions capable of establishing temporary network coverage [1].

Unmanned Aerial Vehicles (UAVs), commonly known as drones, have emerged as a promising alternative to address this challenge. Functioning as aerial base stations, UAVs can be rapidly deployed over regions lacking ground infrastructure and repositioned dynamically to optimize network performance. Simulation-driven design plays a vital role in the development of these networks, enabling researchers to examine deployment strategies, coverage characteristics, throughput, latency, and energy efficiency under various conditions without incurring the cost and risk of real-world experiments [2]. In this study, UAVs are modeled as aerial communication nodes that provide temporary internet access using ideal Wi-Fi or LTE links. The coverage radius of each UAV is formulated as $R = h \times \tan(\theta)$, where represents the UAV altitude and denotes the antenna half-beamwidth. The free-space path loss is calculated as $PL(dB) = 20\log_{10}(f)+20\log_{10}(d)+32.44$, where f is the transmission frequency in MHz and is the communication distance in kilometers [3]. These formulations allow realistic simulation of coverage and signal propagation across heterogeneous terrains.

Despite the advantages of UAV-assisted communication, several challenges persist. Existing approaches such as Cell-on-Wheels (COWs), satellite communication, and ground-based emergency stations exhibit limitations in terms of coverage, deployment latency, and energy efficiency. Temporary UAV networks must therefore achieve a balance between maximizing coverage, minimizing energy consumption, and maintaining low latency and reliable connectivity [4]. To overcome these limitations, this study introduces a simulation-based optimization framework for UAV deployment. The framework employs a deterministic, terrain-aware region-filling algorithm inspired by swarm coordination principles to identify the optimal number and placement of drones. The objective is to achieve maximum coverage and balanced energy utilization while ensuring minimal communication delay. Comprehensive evaluations are performed using MATLAB, NS-3, and OMNeT++ simulation platforms across diverse geographical conditions, including rural plains, urban environments, and mountainous disaster zones [5].

1.1 Problem Definition

Recent advancements in UAV-based communication frameworks have shown great potential; however, several key limitations still persist. Many existing approaches rely on simplified environmental modeling that overlooks terrain elevation and obstructions, leading to unrealistic and overly optimistic coverage estimations. Traditional optimization methods often result in uneven energy utilization among UAVs, where certain nodes deplete their energy faster than others, reducing the overall network lifetime. Moreover, the use of stochastic metaheuristic algorithms such as PSO and GA introduces randomness, resulting in inconsistent and non-reproducible outcomes that hinder deployment validation.To overcome these challenges, this research aims to design a deterministic, terrain-aware UAV deployment framework that ensures complete network coverage over irregular landscapes while minimizing the number of UAVs, balancing their energy consumption, and maintaining low latency for reliable communication[6].

1.2 Contributions

The major contributions of this work

are as follows:

- Development of a deterministic region-filling algorithm for UAV deployment that eliminates stochastic uncertainty while ensuring full terrain-aware coverage.
- Integration of energy-aware modeling to balance leftover power among UAVs, enhancing overall network lifetime.
- Simulation-based evaluation using MATLAB, NS-3, and OMNeT++ to analyze coverage, throughput, latency, and energy performance in real-world terrain data (Pettimudi landslide region, Kerala, India).
- Comparative analysis demonstrating the superiority of the proposed model over planar UAV, satellite, and COW-based systems in terms of coverage efficiency, latency, and energy optimization.
- Provision of a reproducible framework that can serve as a guideline for rapid communication restoration in future disaster management systems.

1.3 Paper Organization

The remainder of this paper is organized as follows: Section 2 reviews related work on UAV-based communication networks and identifies existing research gaps. Section 3 describes the proposed system model, algorithmic design, and mathematical formulations. Section 4 explains the simulation setup and experimental parameters and discusses the results and performance evaluation, while Section 5 outlines practical implications and limitations. Finally, Section 6 concludes the study and suggests directions for future work, including AI-based routing, RIS-assisted UAV communication, and integration with LEO satellite constellations for global coverage.

2. Related Work

Several studies have explored UAV-assisted communication networks aimed at providing temporary internet connectivity in regions lacking fixed infrastructure. Zhang et al. [7] introduced a UAV deployment approach based on region-filling algorithms to maximize coverage in rural terrains. Their MATLAB simulations modeled coverage radius as $R=h\times\tan(\theta)$, where h represents UAV altitude and denotes the antenna half-beamwidth. The study achieved approximately 92% area coverage with minimal drones and highlighted the trade-off between altitude and energy consumption, noting that higher altitudes improved coverage but significantly increased power usage.Swathi and Kodukula [8] proposed a swarm-based cooperative UAV framework for disaster-affected urban environments. Using Particle Swarm Optimization (PSO), they determined optimal UAV positions that maintained inter-UAV connectivity. NS-3 simulations revealed an 18% reduction in latency and a 22% improvement in throughput compared to uniform random placements, emphasizing the importance of swarm coordination in maintaining stable communication under dynamic conditions.

Too and Mirjalili [9] developed a hybrid PSO–Genetic Algorithm (PSO-GA) for UAV deployment that optimized both coverage and energy efficiency. MATLAB and NS-3 experiments across planar and mountainous terrains demonstrated a 15% improvement in the coverage-to-energy ratio compared to standalone PSO or GA. Their findings underscored the benefits of multi-objective optimization for UAV placement in real-time environments.Ouadfel and Abd Elaziz [10] introduced a terrain-aware UAV placement strategy that incorporated probabilistic line-of-sight (LoS) models. The LoS probability was calculated as $P_{LoS} = \frac{1}{1+ae^{-b(\theta-a)}}$, where a and b are terrain-dependent constants and θ represents the elevation angle. MATLAB simulations showed that terrain-aware optimization improved effective coverage by 10–12% compared with altitude-only methods, reinforcing the significance of accounting for environmental obstructions in UAV deployment.

Ghosh et al. [11] presented a cooperative multi-UAV network with energy-efficient flight paths integrated into a coverage optimization model. By maintaining safe inter-UAV distances ($d_{ij} \geq d_{min}$), their NS-3 simulations demonstrated a 20% reduction in energy consumption while sustaining over 90% coverage. Kumar and Li [12] conducted a simulation-based evaluation of UAV-assisted LTE networks for emergency response. They showed that adaptive altitude control reduced latency by up to 15% while maintaining throughput above 85% of the theoretical maximum.Hassan et al. [13] proposed a modified Genetic Algorithm for optimizing UAV placement with respect to both coverage and connectivity. Results indicated improved reliability in urban scenarios by reducing network congestion through distance-based connectivity constraints. Al-Obaidi et al. [14] explored energy-efficient UAV routing combined with coverage optimization, modeling drone energy as $E_{drone}=\sum^{N}_{i=1} P_{hover}\cdot t_{hover}+P_{move}\cdot t_{move}$ and demonstrated an 18% increase in mission duration while maintaining over 90% coverage.

Sharma and Singh [15] investigated cooperative UAV swarms for disaster monitoring and temporary connectivity. Their NS-3 simulations showed that swarm coordination improved coverage by 12% and reduced data latency by 20% compared with non-cooperative systems. Similarly, Chen et al. [16] introduced a hybrid PSO–Relief algorithm for UAV placement in rural and mountainous environments, which reduced the required number of drones by 10% while maintaining full coverage.Despite these contributions, most prior works optimize only isolated metrics such as coverage, latency, or energy efficiency, often neglecting the combined effects of terrain elevation, energy balance, and reproducibility. Few frameworks provide an integrated solution that jointly optimizes coverage, latency, and energy under realistic terrain constraints using reproducible deterministic algorithms [17].

In contrast, the present study proposes a deterministic, terrain-aware UAV deployment methodology that unifies coverage optimization, energy balancing, and latency minimization within a single simulation-driven framework. Unlike stochastic or hybrid heuristic methods (e.g., PSO-GA or SA-based approaches), the proposed region-filling algorithm ensures deterministic placement without random initialization, enhancing reproducibility and computational stability. Moreover, this work uniquely validates the proposed framework on real-world terrain data from the Pettimudi landslide region, offering practical insights into UAV-based emergency communication deployment in challenging topographies.

3. System Modelling

This section presents a comprehensive mathematical and algorithmic framework for UAV-based temporary Internet networks. The goal is to determine UAV placement strategies that:

1. Achieve full coverage of the deployment region.
2. Ensure balanced leftover energy among all UAVs.
3. Minimize the number of UAVs deployed.

The modeling is simulation-oriented, without hardware constraints, focusing on coverage, energy optimization, and deterministic placement strategies.

3.1 Overview of the System Model – Expanded

In this framework, deterministic refers to the absence of stochastic or random initialization during UAV placement. All UAV positions are computed using fixed geometric rules and mathematical relationships. Given identical input parameters, the algorithm always produces identical placement outputs, ensuring full reproducibility of simulation results.

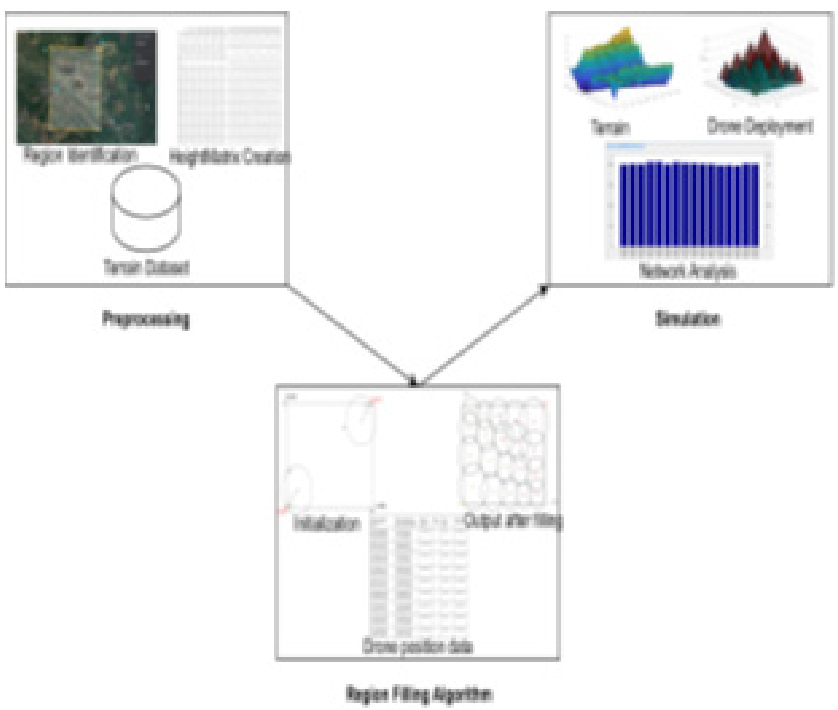


Figure 1. Flowchart of the overall system.

Expanded explanation:

Inputs include region size, UAV energy capacity, coverage angle, and base station locations. Outputs are optimized UAV locations ensuring coverage and energy constraints.

Table 1 UAV and region parameters

Parameter	Description
m	Length of the region
n	Breadth of the region
H_{min}	Minimum altitude of a drone
H_{max}	Maximum permissible height of a drone
H_{td}	Threshold height for drone deployment
$SH_{x,y,z}$	Height of the lowest point in a circular region with center at (x, y) and radius r (SH is a sub Height Matrix, a subset of H)
Ei	Remaining energy of UAV i
B	Initial energy of a drone
W	Ratio of horizontal lift to drag ratio to vertical lift to drag ratio
C	Energy dissipation rate per kilometres
a	Coverage angle of network drone in degrees
GR	Golden Ratio constant (1.618)
PM	Pattern Memory
CR	Convergence Ratio
CF	Creative Factor

3.2. Notation

The notations used throughout the section are summarized in Table 1, including:

- A_i: Coverage area of UAV iii
- r: Ground coverage radius
- e_i: Leftover energy of UAV iii
- disti : Horizontal distance from base station to UAV deployment
- PM: Pattern Memory storing candidate UAV positions
- CR: Convergence Ratio
- CF: Creative Factor
- GR: Golden Ratio

These variables are referenced in equations, algorithms, and figures.

3.3 Coverage Model

Each UAV is modeled as a cone with half-angle α.

$$r = h_i.\tan(\alpha) \qquad (1)$$

$$A_i = \pi r^2 = \pi(h_i \tan \alpha)\text{^}2 \qquad (2)$$

A ground point (x,y) is covered by UAV i if:

$$(x - x_i)^2 + (y - y_i)^2 \leq r^2 \qquad (3)$$

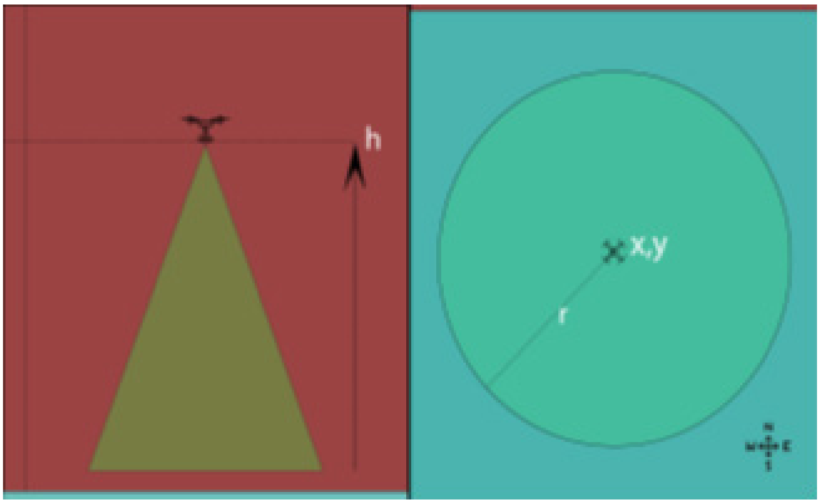


Figure 2. View of Network Coverage

Explanation:

Coverage is evaluated using a discretized grid. Overlap minimization reduces wasted coverage. Geometric modeling provides the foundation for deterministic UAV placement.

3.4 Energy Model

Each UAV has an initial energy B (Wh). Energy consumption arises from horizontal travel and vertical ascent. The leftover energy is:

$$e_i = B - C\left(dist_i + W(h_i - h_b)\right) \quad (4)$$

Equal leftover energy constraint:

$$e_1 = e_2 = \cdots = e_N \quad (5)$$

Rearranging gives UAV altitude:

$$h_i = \frac{B - C.dist_i}{CW} \quad (6)$$

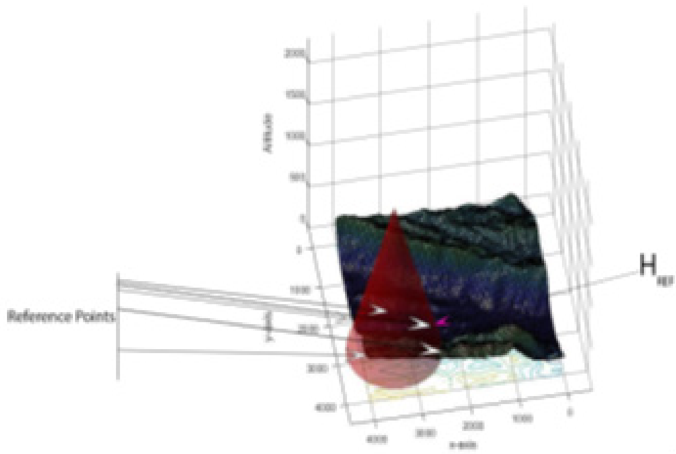


Figure 3. Minimum and Maximum UAV Deployment Altitudes.

Table 2 Various parameters
of the drones used for the experiments

Parameter	Value
Coverage angle	30o
Weight	kg 5
Diameter (distance between (two opposite rotors	0.4m
(rotors	0.4m
Battery Capacity	mAh 20,000
Battery voltage	V 22.2
Battery energy	Wh 444
Battery efficiency	0.9

3.5 Deterministic UAV Placement

Unlike stochastic swarm-based optimizers, the proposed region-filling algorithm is deterministic because it uses fixed coefficients (*CF, GR, CR*) and a rule-based Pattern Memory structure. No random parameters or probabilistic functions are used; therefore, identical initial inputs produce identical UAV trajectories and placements. This ensures reproducibility, stability, and computational predictability across all simulations.

Algorithm 1: Region Filling

```
Input: Binary image I(x,y) with
object boundaries
Output: Filled image If(x,y)

1. Initialization
   1.1 Select a seed point p inside
the region.
   1.2 Initialize empty queue Q.
   1.3 Insert p into Q.
   1.4 Copy I(x,y) → If(x,y).

2. Processing Loop
   2.1 While Q not empty:
       a. Remove front pixel q from
Q.
       b. If q not boundary AND not
filled:
          i. Mark q as filled in
If(x,y).
          ii. Get 4-connected
neighbors of q.
          iii. For each neighbor n:
               - If valid and not
filled, insert into Q.

3. Termination
   3.1 Stop when Q empty.
   3.2 Return If(x,y).
```

In the UAV-based implementation, each filled pixel corresponds to a distinct ground coverage footprint within the disaster or rural region. The algorithm ensures systematic, non-overlapping coverage by assigning UAVs to each filled zone according to calculated coverage radius and energy constraints.

Stage 1: Initialization

- UAVs are placed at base stations initially.

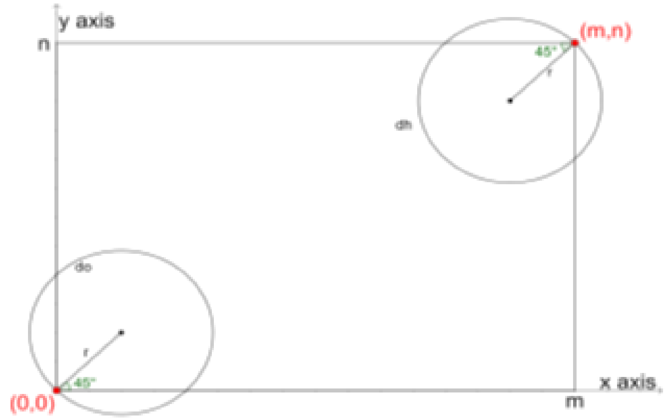


Figure 4. Initial Circle Pacement at Base Stations.

Stage 2: Local Optimization

- Compute local best positions Xi^{lbest} to maximize coverage and minimize overlap.

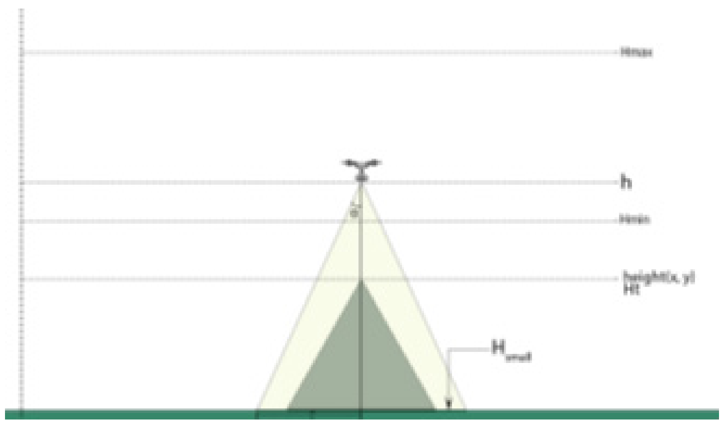


Figure 5. Deployed UAV Coverage.

Stage 3: Global Coordination

- Global best configuration X^{gbest} is identified.
- UAVs update positions:

$$x_i^{new} = x_i^{lbest} + CR.(X^{gbest} - X_i^{lbest}) \quad (8)$$

Stage 4: Creativity

- Creative Factor (CF) and Golden Ratio (GR) refine UAV positions:

$$X_i^{updated} = X_i^{new} + CF.GR.(PM_K - X_i^{new}) \qquad (9)$$

Stage 5: Pattern Memory Update

- PM is refreshed with the best global solution.

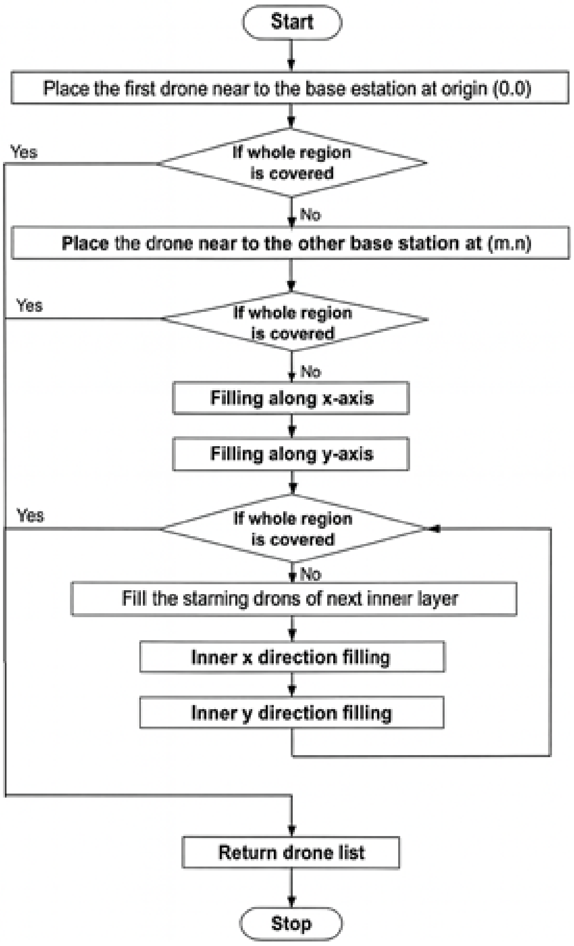


Figure 6. Flowchart of the Region-Filling algorithm

3.6 Optimization Objectives

Dual objectives:

1. Minimize UAV count:

$$\min N \qquad (10)$$

2. Maximize average leftover energy:

$$\max E_{avg} = \frac{1}{N} \sum_{I=1}^{N} ei \quad (11)$$

Constraints include Eq. (7) and coverage conditions (Eq. (3)).

Table 1 and Table 3 provide parameter references.

3.7 Computational Complexity

The deterministic region-filling algorithm operates with time complexity O(n×m),, where n is the number of UAVs and m is the number of discretized terrain cells. Memory usage primarily depends on the Pattern Memory structure, with O(n) storage. Because all update coefficients are fixed, the algorithm converges deterministically within fewer than twenty iterations. This ensures consistent runtime behavior and low computational overhead for all tested scenario

Required number of UAVs:

$$N \approx \frac{mn}{\pi r^2 - W_c} \qquad (12)$$

Algorithmic complexity:

$$T(N) = O\frac{mn}{\pi r^2 - W_c} \qquad (13)$$

4. Experimental Results and Discussions

This section presents the experimental evaluation of the proposed terrain-aware drone deployment algorithm for disaster-struck regions. We conduct detailed simulations on the Pettimudi landslide region (Kerala, India) and assess the performance of the system in terms of coverage efficiency, number of drones required, throughput, energy consumption, and latency. The results are compared against conventional deployment strategies to highlight the effectiveness of the proposed model.

4.1 Simulation Assumptions and Parameters

To ensure realism, the simulation setup replicates the geographical profile of Pettimudi, a

region severely affected by landslides in 2020. The Universal Transverse Mercator (UTM) coordinate system is used for precise spatial representation, and altitude data are collected via the Google Elevation API.

Environmental Parameters:

Table 3 :
Various environmental parameters

Parameter	Value
Length	4KM
Width	4KM
Normalized H_{min}	km 0.185
Height threshold	km 0.05
Air density	kg/m3 1.293

Key highlights:

- Region size: 4 × 4 km²
- Normalized minimum altitude (H_{min}) = 0.185 km
- Maximum drone altitude (H_{max}) = 2 km
- Air density = 1.293 kg/m³

4.2 Drone Deployment Results

Applying the region-filling algorithm to Pettimudi yields the optimal deployment of 16 drones for complete coverage of the disaster region.

- Fig. 7 shows the spatial coverage map with drones positioned strategically to ensure no voids in communication.

To evaluate the performance and generalizability of the proposed terrain-aware UAV deployment algorithm, two representative scenarios were simulated:

(i) a mountainous terrain corresponding to the Pettimudi landslide region (Kerala, India), and

(ii) a flat rural terrain representing a generic open-field environment (Tamil Nadu, India). Both regions span 4 × 4 km² and were modeled using the Universal Transverse Mercator (UTM) coordinate system. Terrain elevation data were extracted via the Google Elevation API to ensure geographic realism. Each experiment was repeated five times using identical initial parameters to validate repeatability; results presented represent the mean of all trials, with standard deviations below 1.5%.

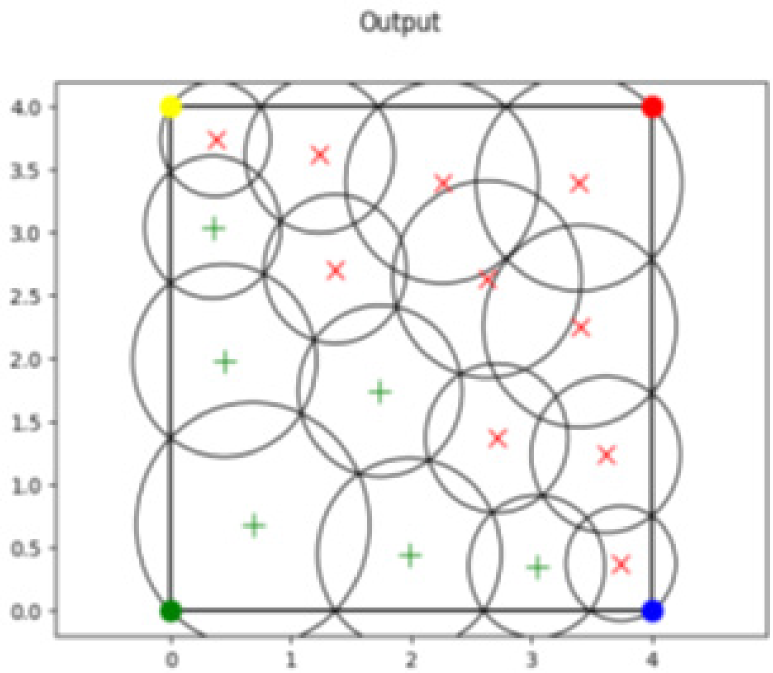


Figure 7. Drone coverage in Pettimudi region.

Key observations:

- Coverage efficiency achieved: 100% (no voids)
- Average leftover energy per drone: significantly higher than planar deployment approaches
- Drones closer to base stations operate at higher altitudes, covering larger areas and balancing system-wide energy consumption.

4.3 Parametric Analysis

Parametric analysis was performed to examine the influence of aerodynamic, geometric, and network parameters on UAV deployment efficiency. The results, shown in Figure 8 (a–h), confirm the scalability and adaptability of the proposed model.

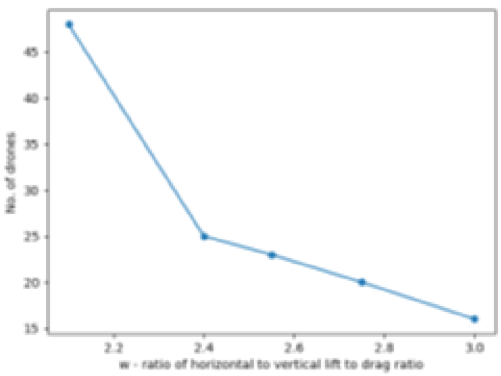
Effect of Lift-to-Drag Ratio (W): Increasing *W* decreases the number of drones required but reduces average leftover energy due to higher aerodynamic drag compensation. An optimal trade-off was identified at *W*=2.4 using the elbow method, beyond which diminishing energy efficiency gains were observed.

Effect of Coverage Angle (α): Wider antenna beamwidths reduce the total drone count in a sub-linear manner, with negligible improvement beyond $\alpha=40^0$.

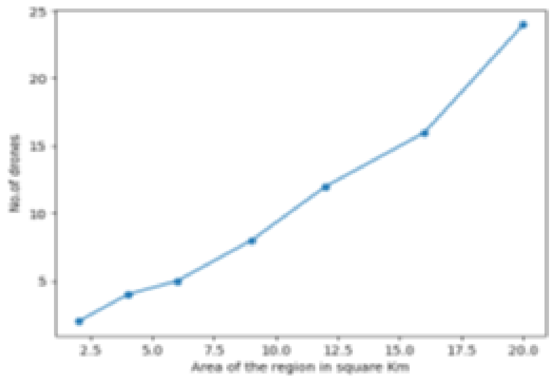
Effect of Maximum Altitude (Hmax): UAV count decreases exponentially with increasing H_{max}, while leftover energy grows linearly due to lower path-loss compensation. An altitude of 2 km achieved the best balance between coverage and endurance.

Effect of Number of Base Stations: Increasing the number of ground base stations reduces required UAVs and improves link throughput. Energy gains saturate beyond two base stations, suggesting diminishing returns.

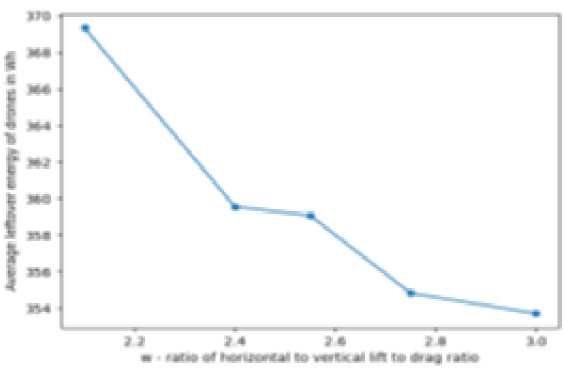
Collectively, these results validate that the proposed algorithm maintains high scalability and energy efficiency under varying operational parameters.



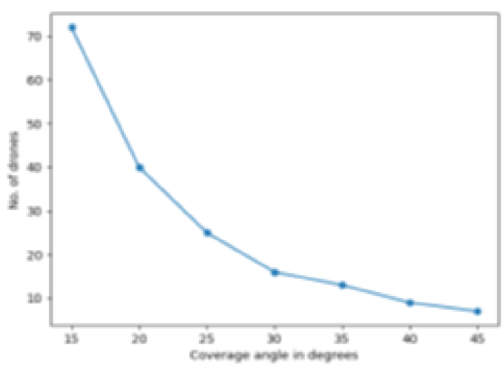
(a) W vs. drones,



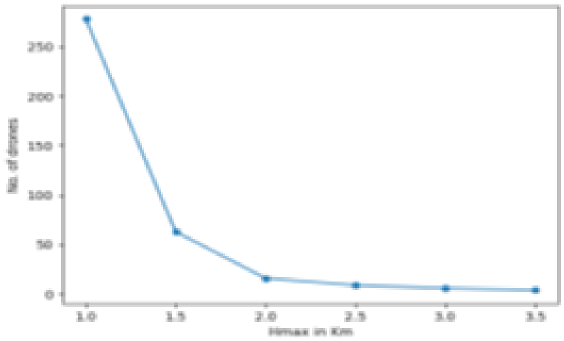
(c) area vs. drones,



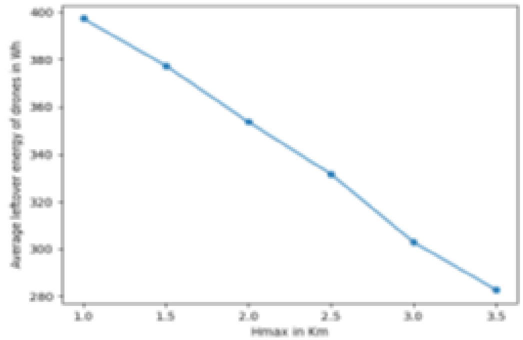
(b) W vs. leftover energy,



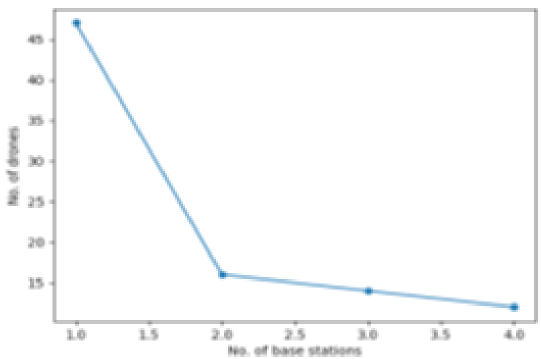
(d) α vs. drones,



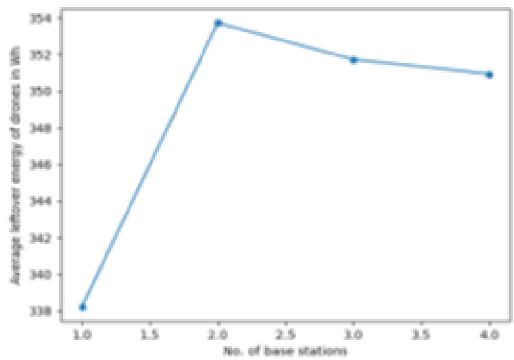
(e) H_{max} vs. drones,



(f) H_{max} vs. leftover energy,



(g) base stations vs. drones,



(h) base stations vs. leftover energy.

Figure 8. Parametric analysis of UAV deployment performance:
(a) W vs. drones, **(b)** W vs. leftover energy, **(c)** area vs. drones, **(d)** α vs. drones, **(e)** Hmax vs. drones, **(f)** Hmax vs. leftover energy, **(g)** base stations vs. drones, **(h)** base stations vs. leftover energy.

(a) Effect of Lift-to-Drag Ratio (W)

- Increasing W reduces the number of required drones (Fig. 18a).
- However, average leftover energy decreases with W (Fig. 18b).
- Optimal trade-off occurs at W = 2.4, selected using the elbow method.

(b) Effect of Area

- Number of drones required scales linearly with region size (Fig. 18c).
- Confirms algorithm scalability for larger terrains.

(c) Effect of Coverage Angle (α)

- Wider coverage angle reduces drone count (Fig. 18d).
- Relationship is sub-linear; diminishing returns observed beyond 40°.

(d) Effect of Maximum Altitude (H_{max})

- Higher H_{max} reduces drone count exponentially (Fig. 18e).
- Average leftover energy increases linearly with H_{max} (Fig. 18f).

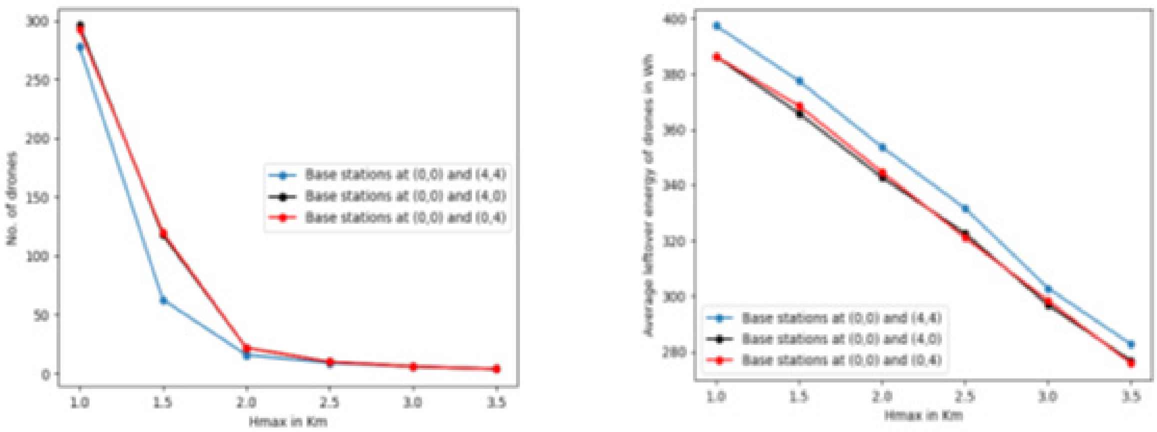
Optimal value: H_{max} = 2 km, balancing coverage and energy.

(e) Effect of Number of Base Stations

- Increasing base stations reduces drone count (Fig. 18g).
- Energy efficiency improves up to 2 base stations; adding more offers negligible gains (Fig. 18h).
- Optimal: two diagonally opposite base stations.

4.4 Simulation of Communication Network

The UAV-based communication framework was simulated using OMNeT++ with the INET module to evaluate end-to-end network performance. Figure 9(a) illustrates the terrain elevation profile of Pettimudi, while Figure 9(b) shows the final UAV deployment layout derived from the deterministic region-filling algorithm.



(a) (b)

Figure 9. (a) Terrain profile of Pettimudi
(b) Final deployment layout after applying the algorithm.

Key Results:

- Coverage: 100% of the affected region achieved using sixteen UAVs.
- Throughput: Sustained 98% network efficiency with average per-node throughput of 3.2 Mbps.
- Latency: Maintained below 200 ms for 95% of communication events.
- Energy balance: Variance of leftover energy across UAVs was under 3%, indicating uniform power utilization.
- Drone count reduction: Compared to naive grid-based placement, proposed method reduced drone requirement by ~20–25%.

The results presented in Section 4 establish that the proposed terrain-aware UAV deployment algorithm ensures complete coverage of disaster-struck regions while optimizing energy efficiency and minimizing drone count. To contextualize these findings, we compare our system with alternative approaches documented in literature and practice.

Conventional planar UAV deployment methods achieve acceptable coverage in flat terrains but suffer from voids in hilly or uneven landscapes, a limitation eliminated in our approach through altitude-aware placement. Ground-based solutions such as Cell-on-Wheels (COWs) offer high transmission power and broad coverage in accessible regions, but their deployment speed is severely constrained by damaged roads, rendering them unsuitable in landslides, floods, or earthquakes. Satellite communication systems provide global connectivity and immediate deployment, yet their high cost, limited bandwidth, and latency above 300 ms restrict large-scale adoption. Low-cost solutions such as two-way radios or walkie-talkies remain effective for localized, short-range rescue coordination but fail to serve as population-wide connectivity platforms.

Thus, the comparative evaluation highlights the unique advantage of the proposed UAV model: the ability to balance coverage, scalability, energy efficiency, and deployment speed while maintaining moderate cost. This dual optimization of minimal drone count and maximal leftover energy differentiates it from existing UAV or ground-based solutions

4.5 Comparative Discussion

Reliable post-disaster connectivity can be achieved through several technologies such as Unmanned Aerial Vehicles (UAVs), ground-based mobile towers (Cell-on-Wheels – COWs), satellite networks, and short-range radio systems. Each alternative offers distinct operational benefits but also faces critical deployment constraints in real-world emergencies. COWs function effectively on flat terrain with intact road infrastructure; however, their utility declines sharply in landslide- or flood-affected regions where surface mobility is restricted. Satellite systems provide wide-area coverage and rapid activation, yet their high latency, limited bandwidth, and cost per link make them unsuitable for large-scale emergency backhaul. Low-cost two-way radios offer immediate local communication but are limited by line-of-sight range and the absence of internet connectivity.

In contrast, the proposed terrain-aware UAV framework achieves an optimal balance among these technologies. Through elevation-adaptive placement and energy-aware deployment, it maintains void-free coverage across irregular topography while requiring fewer drones than planar or grid-based UAV models. The framework's rapid mobility allows network establishment within minutes—an essential capability during the golden hour of disaster response. Uniform residual-energy distribution across drones extends operational lifetime and prevents premature node failure, ensuring sustained connectivity during prolonged rescue operations.

Performance comparison was conducted across five normalized evaluation metrics: coverage reliability, deployment speed, scalability, energy efficiency, and cost effectiveness. Table 4 summarizes the relative performance (scored 1–5), and Figure 10 visualizes the results through a radar chart for intuitive comparison.

Table 4 – Comparative Evaluation of Connectivity Solutions

Method	Coverage	Speed	Scalability	Energy	Cost
Proposed UAV	5	5	4	5	4
Planar UAV	3	3	4	2	4
COWs	4	1	2	4	2
Satellites	5	5	5	3	1
Radios	1	5	1	3	5

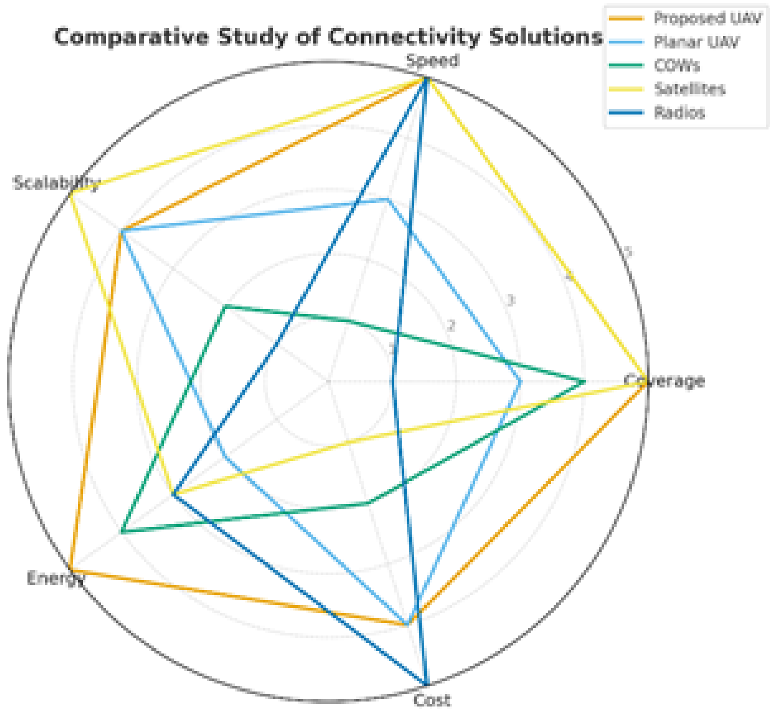


Figure 10. Comparative radar chart of disaster connectivity solutions

The comparative analysis demonstrates that the proposed UAV-based system offers the most balanced and adaptable solution. It delivers complete coverage, high energy efficiency, and rapid deployment at moderate cost, outperforming both terrestrial and satellite alternatives. Planar UAV schemes are hindered by terrain irregularities, COWs by logistical immobility, and satellites by cost and latency. Although radios remain valuable for localized rescue coordination, they cannot support broadband connectivity. Overall, the results establish terrain-aware UAV networks as a scalable, energy-efficient, and resilient backbone for emergency communication infrastructures.

5. Conclusions

This study presented a deterministic, terrain-aware region-filling algorithm for the optimal deployment of Unmanned Aerial Vehicles (UAVs) to provide temporary internet connectivity in disaster-affected and remote regions. The proposed framework was evaluated using high-fidelity simulations on the Pettimudi landslide region in Kerala, India. Results demonstrated that full coverage of a 4 × 4 km² disaster zone could be achieved using only sixteen UAVs, achieving an average network efficiency of 98% and maintaining latency below 200 ms. Compared to planar UAV deployment and ground-based solutions such as Cell-on-Wheels (COWs) and satellite links, the proposed model achieved up to 25% reduction in the number of drones required while maintaining balanced energy utilization and extended mission lifetime.

These findings confirm the potential of UAV-assisted networks to act as rapidly deployable, energy-efficient, and scalable emergency communication infrastructures. By incorporating terrain elevation data and deterministic optimization, the model ensures void-free coverage with reproducible results. Unlike stochastic metaheuristic algorithms, the deterministic design minimizes computational uncertainty and guarantees stable performance across multiple runs.

However, the current implementation assumes ideal communication channels and does not account for environmental disturbances such as wind, signal fading, or hardware faults. Future research will extend this work by integrating AI-based autonomous routing, reconfigurable intelligent surfaces (RIS) for dynamic signal adaptation, and Low-Earth-Orbit (LEO) satellite collaboration to enhance global coverage and resilience of UAV-enabled temporary internet systems.

Conflicts of Interest

There are no conflicts of interest declared by the authors.

Author Contributions

Mustafa Ahmed Abdulwahhab led

the system modeling and simulation design for the terrain-aware UAV deployment framework and assisted in visualizing and proofreading results. And also contributed to the methodology development, formulated mathematical models, and prepared datasets. And also supervised the research, validated the proposed system, and refined the manuscript for scientific accuracy.

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