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3D Deployment of multi-UAV network in Disaster Zones to achieve Coverage and Connectivity

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Abstract—**In disaster situations, effective communication faces challenges due to potential damage of terrestrial base stations, hindering emergency services, and search and rescue missions. Unmanned Aerial Vehicles (UAVs) offer a promising solution, providing anytime, anywhere service by quickly forming temporary networks as base stations for wireless communication. For these UAVs to play a pivotal role in critical missions, strategic placement becomes paramount, considering factors such as user positions, communication range, path loss, transmission power, and coverage. Streamlining deployment efficiency becomes inseparable from the necessity of attaining optimal coverage using a minimal number of UAVs, a crucial consideration given the potential resource constraints in disaster scenarios. Furthermore, UAV ad-hoc formations provide a flexible and robust solution for establishing communication networks in disaster-stricken areas, offering expanded coverage, redundancy, adaptability, and scalability to meet the dynamic challenges posed by such situations. This study delves into an optimal deployment strategy for disaster missions, emphasizing the use of a minimum number of UAVs to provide wireless services to victims and responders. A mathematical model is derived in this study that considers feasible points, calculating the optimal number of UAVs and determining their 3D coordinates while adhering to specified constraints. The optimization problem is formulated as a Mixed-Integer Linear Programming (MILP), concurrently evaluating the number of users served by each UAV. Compared to existing research, this study is specific to the disaster environment, and strikes a good balance between optimal deployment and user coverage by ensuring ad-hoc connectivity.**

Keywords—Coverage, Connectivity, Deployment, Disaster, Unmanned aerial vehicle, Users.

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have become integral in diverse wireless network applications, offering unparalleled advantages [1], [2]. Their inherent mobility, flexibility, and adaptability to varying altitudes position them as promising platforms for base stations, significantly enhancing coverage. When deployed as base stations, UAVs contribute to the improvement of both coverage and network capacity, presenting scalable solutions that easily accommodate the addition or removal of UAVs. In emergency situations like disasters, especially when terrestrial base stations are compromised, or destroyed, UAVs emerge as the preferred choice for aerial base stations offering a cost-effective and rapid solution [3], [4]. Their ability to operate without relying on fixed infrastructure makes them invaluable during critical moments particularly crucial in the initial hours of disasters, where timely communication can be a determining factor in response effectiveness. Operating at elevated heights, they establish Line of Sight (LoS) connections with users, overcoming obstructions that ground-based solutions may face and thereby providing enhanced coverage [5].The study in [6] finds that the utilization of low altitude platforms (LAPs) in wireless emergency networks leads to a generally lower total number of required base stations for effective coverage in disaster scenarios, highlighting the efficiency of LAPs in reducing resource needs.

While leveraging UAVs as base stations presents numerous advantages, their effective deployment faces several challenges that need to be addressed. These challenges encompass energy constraints, path loss, user requirements, Quality of Service (QoS), air-to-ground connections, availability, and altitude of operation. Existing literature includes various studies on the optimal deployment of UAVs for different applications. However, a predominant approach in these studies involves fixing UAVs at a certain altitude and optimizing only the horizontal placement [7], [8]. Necessarily, this results in a 2D deployment, as the altitude remains unoptimized. The authors of [9] established a correlation between altitude and maximum coverage, demonstrating that as altitude increases, path loss also increases. Thus, given that the real-world environment is inherently 3D, optimizing altitude becomes a critical factor for deployment of UAVs as base stations. Numerous studies have explored the 3D placement of UAVs, yet these investigations have primarily focused on identifying effective positions for a given set of UAVs with limited constraints. Furthermore, many of these studies rely on heuristic optimization schemes, introducing challenges such as premature convergence, susceptibility to local minima, and time-consuming computations, affecting result precision [5], [10]. Research on determining the optimal number of required UAVs is sparse. The investigation in [11] focuses on minimizing the number of UAVs for IoT coverage. However, it treats each UAV as an independent entity, lacking the capability to fulfil critical mission requirements. Additionally, the study assumes a uniform distribution of users on the ground, a condition that may not hold in disaster scenarios.

The communication infrastructure among UAVs and the base station is vital for efficient flow of data. Although [12] delves into the connectivity among UAVs in conjunction with optimal deployment, it does not specifically explore data rate requirements, and it adopts a centralized architecture. Centralized architectures face challenges related to the limited range of the area served by UAVs. Therefore, to ensure connectivity with enhanced coverage, establishing multi-hop communication becomes imperative. Consequently, coverage, connectivity, and quality emerge as significant constraints in the optimization problem. To the best of our knowledge, both theoretically and practically, the literature lacks an optimization problem for 3D deployment in disaster monitoring that considers various constraints, including data rate, path loss, and connectivity. This study focuses on optimizing the deployment of UAVs to provide maximum coverage to users while considering key factors such as the number of UAVs, their positions, altitudes, coverage, data rate, and multi-hop ad hoc connectivity. The approach is designed to effectively address the intricate challenges linked to UAV deployment in wireless communication networks. The terms 'users' and 'victims' are interchangeably used in the study.

The paper is structured as follows; Section II conducts a review of existing literature on 3D UAV deployment. Section III details the system model considered in this study, and section IV and V deals with mathematical modelling and constraint linearization respectively. Results of the study are presented in Section VI, and paper is concluded in Section VII, providing insights into future research.

II. RELATED WORKS

The literature on the deployment of Unmanned Aerial Vehicles for wireless communication and network coverage presents diverse approaches and optimization strategies. Several studies have tackled the challenges of optimal drone placement, taking into account multiple factors such as altitude, energy efficiency, target coverage, and connectivity. The work in [13] focused on the minimum cost drone location problem for ground surveillance, considering altitude, energy, and targets. While proposing centralized and localized algorithms, the optimal centralized method had limitations in scalability. The authors of [14] addressed UAV-assisted communication systems, optimizing 3D positions, user clustering, and frequency band allocation. Their approach aimed to minimize UAVs while meeting quality of service constraints. A 3D UAV-BS placement for wireless cellular services is introduced in [15], optimizing coverage for users with diverse quality-of-service requirements. The study included an exhaustive search for optimal altitude and proposed the Maximum Weighted Area (MWA) algorithm. The authors also proposed an optimal 3D placement algorithm in [16] for maximizing user coverage with minimal transmit power. In [17], a 3D deployment algorithm for multiple UAVs is presented, optimizing total network throughput with statistical user positions. The centralized scheme employed a virtual force field and the particle swarm optimization algorithm for vertical coordinates. An adaptive UAV deployment scheme for wireless connectivity is discussed in [8], optimizing UAV position based on instantaneous traffic. It enhances throughput and success probability, surpassing non-adaptive approaches, especially in low-traffic scenarios. The authors of [11] suggested an efficient method to optimize UAV positions for wireless network user coverage, considering the minimum number of UAVs and their optimal positions. However, the study treated UAVs as independent entities with no peer-to-peer communication.

The work presented in [18] explored the deployment challenges of drone base stations (drone-BSs) for network coverage, investigating the impact of different wireless backhaul types. The study considered both network-centric and user-centric approaches for optimal 3D placement. The authors also introduced a heuristic approach in [5] to determine the minimum number and 3D placement of UAV base stations for optimal coverage in an area with varying user densities. The authors of [19] focused on optimizing the deployment of drone small cells (DSCs) for wireless services, determining the optimal height to provide maximum coverage at minimal transmit power. A 3D placement problem considering both vertical and horizontal mobility of drone-cells is formulated in [20], aiming to maximize network revenue by optimizing coverage area and altitude. In [21], an optimization problem for deploying UAVs as small cell base stations in IoT networks is presented, minimizing their number while maximizing coverage. The work in [22] investigated the optimal deployment of multiple UAVs as wireless base stations for ground user coverage by calculating downlink coverage probability considering altitude and antenna gain.

An energy-efficient wireless coverage through optimal Drone Base Station (DBS) deployment is explored in [23], proposing two algorithms for scenarios with equal and unequal transmit power allocation. The authors of [10] addressed the fast deployment challenges of heterogeneous UAVs for wireless coverage, focusing on minimizing deployment delays. A two-layer optimization method is introduced in [24] for jointly optimizing UAV deployment and task scheduling to minimize system energy consumption. A similar approach is presented in [25] to jointly optimize the deployment height and path loss compensation factor of aerial base stations for maximizing user coverage in uplink transmission. The authors of [26] presented an innovative framework for efficient deployment and mobility of multiple UAVs, optimizing energy-efficient uplink data collection from ground IoT devices.

The placement of a heterogeneous set of UAVs to optimize wireless coverage for ground users in a designated area is studied in [27], but did not consider connectivity between UAVs. The work presented in [9] contributed to optimizing LAP deployment for efficient wireless communication, but the approach treated UAVs as independent entities. The authors of [28] sought to minimize the MBS count for wireless coverage of distributed ground terminals. An energy-efficient optimization is addressed in [29] for a UAV-enabled IoT network, employing modified global K-means, successive convex approximation, and successive linear programming techniques. The authors of [12] tackled deploying UAVs for network access to ground targets, minimizing cost and UAV altitudes, considering various communication aspects and centralized connectivity to the base station. The work presented in [30] explored a UAV-assisted disaster scenario, maximizing user-UAV connections while ensuring minimal user connectivity using Integer Linear Programming (ILP). A Backhaul- and - Coverage - Aware Drone Deployment problem in rural areas is addressed in [31] and focused on connectivity through signal-to-noise ratio thresholds. However, data rate requirements and altitude bounds are not incorporated in the work.

III. SYSTEM MODEL

The study considers a disaster environment where terrestrial base stations are damaged or destroyed, and users in groups, deprived of any communication means are seeking for emergency services. In such scenarios, UAVs offer a dynamic and rapidly deployable solution for restoring wireless communication. It is assumed that the approximate positions of these users are known, obtained through an initial scanning of the area, which falls beyond the scope of this study. With the positions known, the study aims to determine the optimal deployment of UAVs to efficiently serve these users. To achieve this objective, there are two important questions to be addressed,

1. What is the optimal number of UAVs required to provide emergency services to the victims?

2. What are the efficient 3D positions for UAV deployment to ensure maximum user coverage?

The altitude of operation is a critical factor in achieving maximum coverage. Higher altitudes may reduce the number of UAVs needed, covering a larger area to serve more victims, but could result in increased path loss and potential data rate issues. Conversely, lower altitudes may require more UAVs for effective coverage. Hence, determining the optimal altitude involves calculating a trade-off between coverage and path loss within specified altitude bounds (H_{min}, H_{max}), where H_{min} and H_{max} represents the minimum and maximum safe altitudes for the UAVs respectively. While the study explicitly considers path loss for UAV positioning, it is important to note that path loss has an indirect impact on the required number of UAVs. An additional critical constraint for the placement problem involves maintaining connectivity among the UAVs to uphold an active ad-hoc network. As the UAVs hover over key locations for damage assessment and monitoring, relaying crucial information to response teams, it is essential that they stay connected. To ensure this connectivity, each UAV must be linked with at least one of its peers or to the base station. Consequently, the communication range of the UAVs sets an upper limit on the altitudes at which they can effectively operate.

In the context of a disaster environment, the essential data rate for users involves communicating with the first line responders, transmitting critical messages such as distress signals (SoS) or requests for emergency medical aid and food supplies. Given that these services do not demand high data rates, equal data rates are considered for all users. Additionally, it is assumed that all users have equal bandwidth and transmit power. The primary objective of this study is to identify the optimal number of UAVs and their corresponding 3D positions that minimize path loss while adhering to data requirements and other relevant constraints. The study considers free space and Line of Sight (LoS) communication. This assumption is consistent with similar considerations made in references [32], [33]. The objectives and the constraints are formulated as an optimization problem that solves a mathematical model to optimize number of UAVs N and the efficient positions (x_i, y_i, z_i) for each UAV $i \in N$. Given the numerous variables in the study, dealing with a multitude of feasible solutions can make the optimization process complex and time-consuming. To streamline this without sacrificing optimality, a smaller sample space is calculated, consisting of 2D feasible points that are then fed into the model. These 2D points represent potential shadow locations of UAVs on the ground. The model subsequently selects the optimal N feasible points and determines their effective altitudes. However, the challenge lies in determining the set of feasible 2D points. Unlike scenarios where users are uniformly distributed, disaster environments often exhibit clustered user formations. The centroids of each cluster can be considered as feasible 2D points for optimization. To address this, K-means clustering is employed to group users based on distance. This approach streamlines the feasible point selection process. Increasing the number of feasible points provides a more comprehensive representation of the disaster scenario, taking into account the clustered nature of users and enhancing the accuracy of the optimization process.

IV. MATHEMATICAL MODELING

Assuming that the feasible set of 2D deployment solutions are available, the optimization problem must select N number of best fit points, and then determine the altitude at which path loss is minimum such that maximum users are served. To accomplish this goal, the optimization model introduces multiple decision variables. To initiate the process, it is important to ascertain the selection status of a feasible point. A binary decision variable p_i is introduced, taking a value 1 if the point is selected, and 0 otherwise. The model then calculates the optimal value of h_i for the selected point, ensuring that this value falls within the specified bounds of H_{min} and H_{max}. In instances where the point is not selected, its corresponding h_i is set to 0. It is to be noted that the altitude is directly proportional to path loss. To accurately calculate path loss, it is important to determine the association between each user and the corresponding UAV. Thus, the path-loss formula needs to be included into the model. A binary variable u_{ij} is defined, that takes a value 1 if user j is served by UAV i, and 0 otherwise. Let L_{ij} be a continuous variable that denotes the path loss of user j when served by UAV i. Thus, the objective function aims to minimize the number of UAVs as formulated in $(1a)$, subject to various constraints outlined in $(1b)$ through $(1t)$, where I is the total number of UAVs and J is the total number of users.

$$min \sum_{i \in I} p_i \tag{1a}$$

$$\sum_{i \in I} p_i \leq I \tag{1b}$$

$$h_i \leq H_{max} \times p_i \quad \forall i \in I \tag{1c}$$

$$h_i \geq H_{min} \times p_i \quad \forall i \in I \tag{1d}$$

$$\sum_{i \in I} u_{ij} \leq 1 \quad \forall j \in J \tag{1e}$$

$$u_{ij} \leq p_i \quad \forall i \in I, j \in J \tag{1f}$$

$$\sum_{i \in I} \sum_{j \in J} u_{ij} \geq \gamma \times U \tag{1g}$$

$$\sum_{j \in J} r_d \times u_{ij} \leq B \times p_i \quad \forall i \in I \tag{1h}$$

$$\cot(\theta) \times u_{ij} \times d_{ij} \leq h_i \ \forall i \in I, j \in J \tag{1i}$$

$$\left(\frac{4\pi f_c}{c}\right)^2 \left({d_{ij}}^2 + {h_0}^2\right) \leq L_{threshold} + \left(1 - u_{ij}\right) M \quad \forall i \in I, j \in J \tag{1j}$$

$$L_{ij} \leq M \times u_{ij} \ \forall i \in I, j \in J \tag{1k}$$

$$L_{ij} \geq \left(\frac{4\pi f_c}{c}\right)^2 \left({d_{ij}}^2 + {h_0}^2\right) u_{ij} \quad \forall i \in I, j \in J \tag{1l}$$

$$C_{ik} \leq p_i, C_k \leq p_k \ i \neq k, \ \forall i, k \in I \tag{1m}$$

$$\left(\frac{4\pi f_c}{c}\right)^2 \left({d_{ik}}^2 + {h_0}^2\right) \leq L_{threshold} + (1 - C_{ik}) M \ \ i \neq k, \ \forall i, k \in I \tag{1n}$$

$$L_{ik} \leq M \times u_{ik} \ \forall i, k \in I \tag{1o}$$

$$L_{ik} \geq \left(\frac{4\pi f_c}{c}\right)^2 \left({d_{ik}}^2 + {h_0}^2\right) C_{ik} \ \ i \neq k, \ \forall i, k \in I \tag{1p}$$

$$\sum_{k \in I} C_{ik} \geq 1 \ \forall i \in I \tag{1q}$$

$$S_{ik} \leq C_{ik} \ \ i \neq k, \ \forall i, k \in I \tag{1r}$$

$$\sum_{i,k\in I} S_{ik} \geq \sum_{i\in I} p_i - 1 \quad (1s)$$

$$\sum_{i,k\in F, i\neq k} S_{ik} \leq |F| - 1 \;\; \forall F \subseteq I, |F| \geq 1 \quad (1t)$$

Constraint (1*b*) ensures that the total number of selected 2D points aligns with the optimal number of UAVs, denoted as N. Constraints (1*c*) and (1*d*) dictate that the altitude of selected points must fall within the bounds of H_{max} and H_{min} respectively, or be set to 0 otherwise. Constraint (1*e*) specifies that each user is served by only one UAV, and (1*f*) ensures that a user is served by a feasible point if that point is among the optimal positions. Constraint (1*g*) mandates that the total number of users served by all UAVs must exceed a specified percentage, denoted as γ, of the total users. A γ value of 1 maximizes coverage. Constraint (1h) imposes a limit on the number of users served by a UAV located at a selected feasible point. Constraint (1*i*) determines that users at a distance d_{ij} from a feasible point with altitude hi are considered served by that UAV only if $h_i \geq \cot(\theta) \times u_{ij} \times d_{ij}$ where θ is the angle of coverage formed at the UAV. A user *i* is not served by UAV *j* if the path loss exceeds the threshold value $L_{threshold}$. This can be written as,

$$u_{ij} = \begin{cases} 0, \left(\frac{4\pi f_c}{C}\right)^2 (d_{ij}^2 + h_i^2) \geq L_{threshold} \\ 0 \; or \; 1, \; Otherwise \end{cases} \quad (2)$$

This is formulated as a constraint in (1*j*) where M is a large positive number [11]. Constraint (1*k*) states that the path loss is set to 0 if user *j* is not served by UAV *i*, and constraint (1*l*) states that, if a user *j* is served by UAV *i* placed at the selected 2D feasible point, the value of L_{ij} must be atleast equal to the path loss at that user from the UAV.

Next set of constraints involve describing the network connectivity among the UAVs. For this, a binary decision variable C_{ik} is introduced which takes values 1 if there exists a connection between UAV *i* and UAV *k*; and 0 otherwise. Another variable S_{ik} is defined to denote if a particular link is selected to be a part of the multi-hop network topology or not. Constraint (1m) states that a connection between two UAVs *j* and *k* can exist only if the points at which the UAVs are placed is selected by the model. A link between two UAVs i and k is chosen only if the path loss between them is below the $L_{threshold}$ and this is defined in (1n). Constraints (1o) and (1p) sets the bounds of $L_{threshold}$; the path loss is 0 if a link between UAVs *i* and *k* does not exist. The constraint that each UAV must have a communication link atleast with one other UAV is represented by (1q). To ascertain connectivity, constraint (1r) is defined which represents that, a link is considered to be a part of the topology only if a connection exists between the two UAVs. Constraint (1s) denotes that for a total of *N* UAVs, there must exist atleast (*N*-1) connections where $N = \sum_{i\in I} p_i$ and $N \in I$. It is implicitly assumed that the point closest to the Ground Control Station (GCS) functions as a relay between the GCS and the UAVs. This point is excluded from the optimization problem. Lastly, the UAVs that are connected or communicate with each other in a way that creates a cycle must be avoided. This is represented in (1t).

The optimization problem incorporates both binary and continuous decision variables, necessitating the use of mixed-integer linear programming (MILP) techniques for its solution. However, widely used ILP solvers like PuLP, CPLEX, and Gurobi exclusively handle linear constraints. Consequently, any non-linear constraints within the problem must be linearized before initiating the solution process.

V. Linearization of Equations

From the above set of equations, (1j), (1l), (1n) and (1p) are non-linear and so, cannot be directly applied as a constraint to the ILP solver. The linear approximation of these equations can be obtained by considering *Taylor expansion*, a way to represent a function as an infinite sum of terms, where each term is obtained by taking the derivatives of the function at a specific point. The *Taylor expansion* of a function is expressed as [11] ,

$$F_{ij}(h_i) = F_{ij}(h_i - h_0 + h_0) \approx F_{ij}(h_0) + F'_{ij}(h_0)(h_i - h_0) \quad (3)$$

From [11], (1j) can be reformulated as,

$$u_{ij} \leq \frac{M - h_i}{M - a_{ij} + \frac{1}{2}} \;\; \forall i \in I, j \in J \quad (4a)$$

Similarly, (1n) can be reformulated as,

$$C_{ik} \leq \frac{M - (h_i - h_k)}{M - a_{ik} + \frac{1}{2}} \;\; \forall i, k \in I \quad (4b)$$

$$\text{where, } a_{ij} = L_{threshold} - \left(\frac{4\pi f_c}{C}\right)^2 ({d_{ij}}^2 - {h_0}^2) \quad (4c)$$

$$a_{ik} = L_{threshold} - \left(\frac{4\pi f_c}{C}\right)^2 ({d_{ik}}^2 - {h_0}^2) \quad (4d)$$

$$h_0 = \frac{H_{max} + H_{min}}{2} \quad (4e)$$

Constraint (1l) is non-linear as it contains the terms ${h_0}^2 \times u_{ij}$. *This* is linearized by applying *Taylor expansion* method and the linear approximation can be represented as,

$$L_{ij} \geq \left[\left(\frac{4\pi f_c}{C}\right)^2 ({d_{ij}}^2 + {h_0}^2) + \left(\frac{4\pi f_c}{C}\right)^2 \times 2 \times h_0 \times (h_i - h_0)\right] u_{ij} \quad (4f)$$

However, the above equation still has the multiplication of $h_i \times u_{ij}$ and needs to be further linearized. Let x_{ij} be a decision variable such that $x_{ij} = h_i \times u_{ij}$. Placing this in the above constraint and solving the equation,

$$L_{ij} \geq \left[\left(\frac{4\pi f_c}{C}\right)^2 ({d_{ij}}^2 - {h_0}^2)\right] u_{ij} + \left(\frac{4\pi f_c}{C}\right)^2 \times 2h_0 \times x_{ij} \quad (4g)$$

In making this assumption, there are few more constraints to be considered.

$$x_{ij} \leq h_i \;\; \forall i \in I, j \in J \quad (4h)$$

$$x_{ij} \leq H_{max} \times u_{ij} \; \forall i \in I, j \in J \quad (4i)$$

$$x_{ij} = h_i - (1 - u_{ij}) H_{max} \;\; \forall i \in I, j \in J \quad (4j)$$

The variable x_{ij} must be zero if u_{ij} or h_i is zero, and x_{ij} is bounded by the maximum altitude H_{max} as defined in (4*h*) and (4*i*). Also, x_{ij} must be equal to h_i if u_{ij} is 1 as defined in (4*j*). Similarly, constraint (1*p*) can be reformulated as,

$$L_{ik} \geq \left[\left(\frac{4\pi f_c}{C}\right)^2 ({d_{ik}}^2 - {h_0}^2)\right] C_{ik} + \left(\frac{4\pi f_c}{C}\right)^2 \times 2h_0 \times y_{ik} \quad (4k)$$

$$\text{where, } y_{ik} = h_i \times C_{ik} \quad (4l)$$

$$y_{ik} \leq h_i \;\; \forall i, k \in I \quad (4m)$$

$$y_{ij} \leq H_{max} \times C_{ik} \; \forall i, k \in I \qquad (4n)$$

$$y_{ik} = h_i - (1 - C_{ik}) H_{max} \;\; \forall i \in I, j \in J \qquad (4o)$$

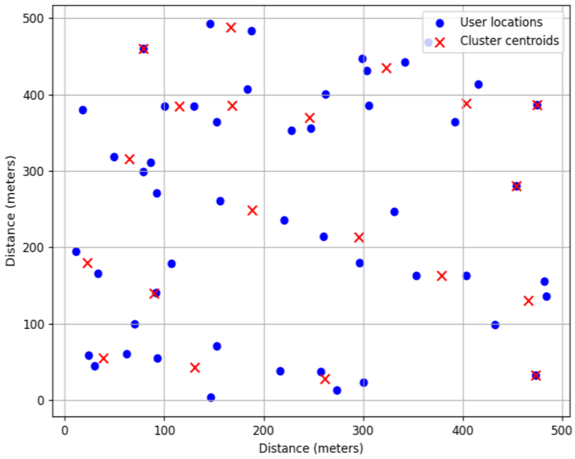

Fig. 1 User distribution and cluster centroids (K=20)

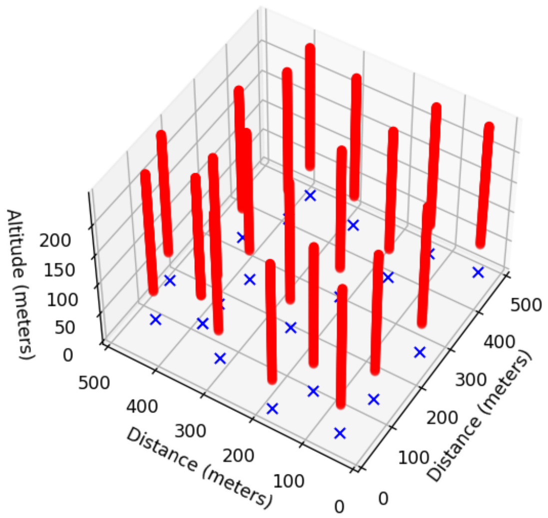

Fig. 2 Continuous range of altitude values for the given centroids

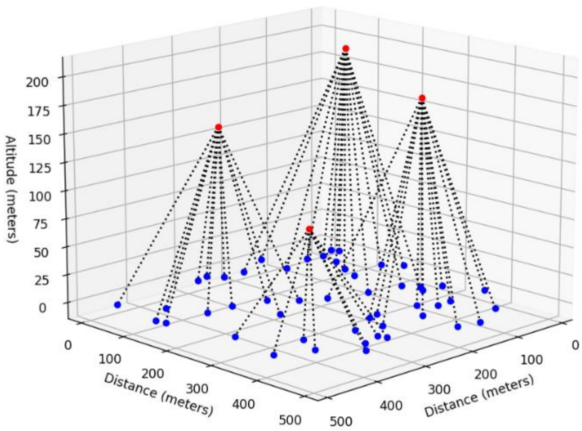

Fig. 3 Optimal altitude obtained by solving the optimization problem (number of users =50)

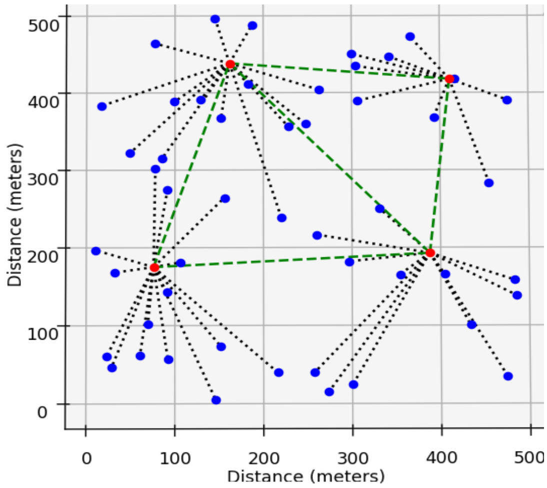

Fig. 4 Connectivity among the UAVs

On solving these constraints in ILP solver, the optimal number of UAVs required and their efficient deployment positions can be obtained. The variables involved in the optimization problem are listed in Table 1.

VI. Numerical Results

The optimization problem is implemented in python using PuLP library on an Intel(R) Core(TM) i5-10300H CPU @ 2.50GHz in Windows OS.

The following sub-sections presents the results on maximum coverage using optimal number of UAVs while providing equal data rate to users. The problem has ensured that every UAV remains connected with atleast one other UAV, and that the links chosen for communication strictly avoids closed cyclic loops. The results for the linear model defined from $(1a)$ through (4o) is presented to show the effective of the study in critical missions such as disasters. While there is a lack of prior studies that have addressed such a comprehensive array of constraints within the optimization problem, the authors of this study have conducted a comparative analysis with relevant research in the realm of optimal 3D deployment. An analysis of the optimal number of UAVs for various user distributions is also presented, along with an analysis of the cost associated with integrating connectivity into the model. This is achieved by comparing the results with those obtained in similar studies that do not consider connectivity constraints.

In our analysis, we modelled a non-uniform distribution of user locations to simulate a disaster scenario, where people may gather up unevenly. We considered a rectangular area of dimensions 500×500 meters and the number of users were varied from 50 to 1000. In this optimization problem, the goal is to cover all the users while meeting the path loss constraints and data rate requirement. Since a disaster scenario is studied, all the users are provided with equal data rates as the services are only provided to meet the emergency communications among the victims and with the first line responders, or the base station. The data rate required by each user is 5 Mbps, and the maximum data rate that a UAV can provide is taken as 300 Mbps. The altitude of the UAVs is limited to H_{max}= 250 meters and H_{min}= 50 meters. An elevation angle of 45° is considered. The mathematical model takes a set of feasible points as parameters. In order to identify the potential points, we employed k-means clustering method on the data points, with the number of clusters determined as α times the number

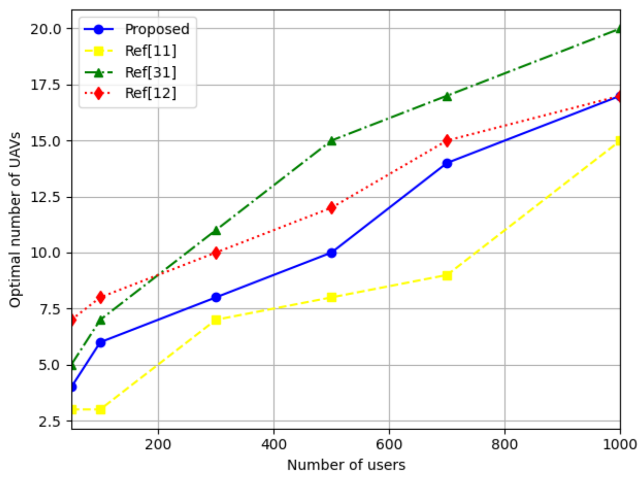

Fig. 5. Required number of UAVs vs. number of users

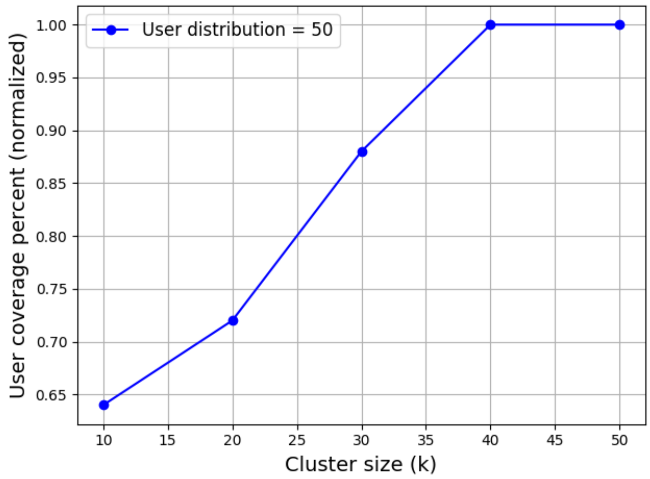

Fig. 6. Cluster size vs. user coverage percent

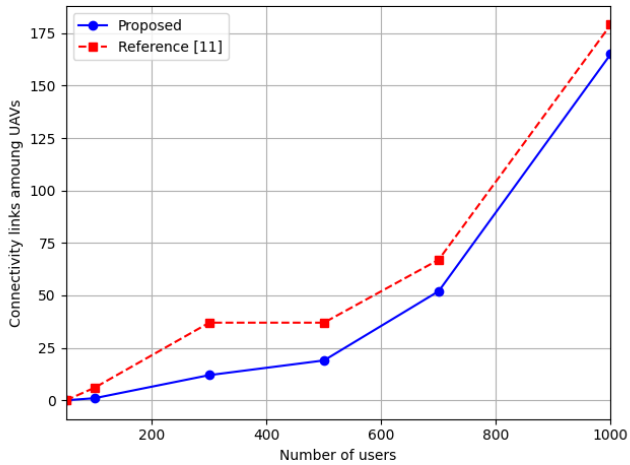

Fig. 7. Number of communication links vs. number of users

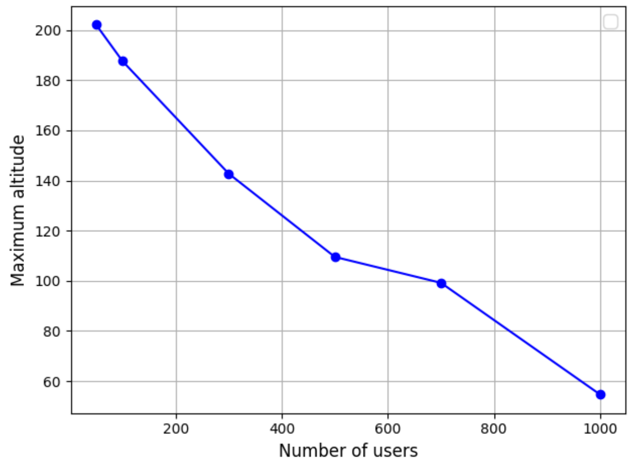

Fig. 8. Maximum altitude vs. number of users

of users, where α ∈ (0.4,0.8). The centroids of these clusters are considered as a set of feasible solutions for our mathematical optimization model. Fig.1 depicts the user distribution and cluster centroids (K=20) for a user count of 50. The pulp library from python is used to solve the linear optimization problem with $(2a)$ as objective subject to constraints $(2b)$ to $(2t)$ and $(4a)$ to $(4o)$. Subsequently, the optimization model determined the optimal number of UAVs and their deployment locations with altitudes within the specified range of H_{min} to H_{max}. The values assigned to the variables are detailed in Table 2. Fig.2 shows the possible range of altitude values for each centroid point, and the optimal altitudes obtained on solving the optimization problem is shown in Fig.3. The connectivity among the so obtained optimal number of UAVs is plotted in Fig.4.

Fig.5 plots the results of the optimization model in terms of optimal UAVs with increasing number of users, and a comparison with state-of-art approaches is also presented. The graph clearly explains that the number of UAVs increases with increasing number of users. This is also influenced by the data rate each UAV can provide, as more is the demand for service, more UAVs will be required. We have also explored the relationship between the number of clusters and its impact on coverage. The analysis is performed by varying the cluster count k and evaluating the percentage of users covered. From Fig.6, it can be observed that, for k< 20 (α < 0.4), a feasible solution was possible for coverage of around 70% while for k ≥ 20 (α ≥ 0.4), complete coverage was possible for a user count of 50. However, as the number of users went higher, α > 0.6 provided efficient coverage of users.at optimal altitudes. This is mainly because, as the number of clusters increases, a greater number of feasible points are generated and fed into the model, leading to a closer approximation of the optimum position, offering efficient coverage.

A significant challenge addressed in the paper is to ensure connectivity among UAVs. To illustrate the relationship between the number of communication links established among UAVs, we have considered a path loss of 350dB as an acceptable threshold. As the number of deployed UAVs increases, the distance between its peers decreases and they tend to remain connected, minimizing the path loss. However, the scenario becomes challenging with sparse user distributions as the model can lead to infeasible solutions. The number of communication links established are plotted in Fig.7 for varying user count. Fig.8 shows a plot of maximum altitude achieved for the UAVs for various user distributions. From the results, we have observed that the altitude of UAVs tends to decrease with number of users. This is because, as the number of users goes high, more UAVs need to be deployed to meet the demand thereby leading to better coverage at comparatively lower altitudes.

TABLE 1 Decision variables

Variable	Description
p_i	1 if point I is selected as an optimal feasible point
u_{ij}	1 if UAV i serves user j
h_i	Altitude of UAV i
d_{ij}	Euclidean distance between UAV i and user j
d_{ik}	Euclidean distance between UAV i and UAV k
C_{ik}	1 if a link exists between UAVs i and k
S_{ik}	1 if a link is selected
L_{ij}	Path loss between UAV i and user j
L_{ik}	Path loss between UAVs i and k
e_{ij}	Auxiliary variable
x_{ij}	Auxiliary variable
y_{ik}	Auxiliary variable

TABLE 2 Parameter values

Parameters	Value
f_c	2×109Hz
C	3×10^{8} Hz
H_{max}	250 meters
H_{min}	50 meters
θ	45°
γ	1
U	50,100,300,500,700,1000
B	300 Mbps
Area	500×500
r_d	5 Mbps

Finally, the results presented in our work is compared with [11] that has not considered connectivity constraints. In doing so, the cost of backhaul connectivity can be analysed. Introducing additional set of constraints enforces that the optimal coverage involves deploying at least the same number of UAVs as in scenarios where connectivity was not considered. The cost of connectivity is thus measured in terms of the additional UAVs required to ensure backhaul connectivity and is recorded in Table 3. It is evident that adding connectivity constraints has increased the number of UAVs, however, it has not compromised on the effective altitude of operation. This is more evident at lower user count and is also a factor of the user locations. On the contrary, as number of users increases, cost of connectivity decreases as the coverage constraints enforces to deploy more UAVs, and backhaul connectivity can more or less be achieved with fewer or zero additional UAVs.

Table 3 Analysis with and without connectivity constraints

Number of users	With connectivity		Without connectivity	
	Number of UAVs	Maximum altitude	Number of UAVs	Maximum altitude
50	4	202.12	2	202.12
100	6	187.54	4	187.54
300	8	142.72	5	142.72
500	10	109.52	9	109.52
700	14	99.19	12	99.19
1000	17	54.64	16	54.64

VII. Conclusion

The research offers valuable insights into optimizing UAV deployment in disaster areas, taking into account various constraints to ensure optimal coverage and connectivity. It introduces a mathematical model, utilizing Mixed-Integer Linear Programming (MILP), to optimize UAV quantity and their 3D coordinates while considering ad-hoc connectivity and addressing constraints. It also discussed the significance of maintaining connectivity among UAVs to ensure an active ad-hoc network, underscoring the need for multi-hop communication for enhanced coverage. Numerical findings reveal the correlation between UAV quantity and user count, showing an increase in UAVs with a higher number of users. Furthermore, the results demonstrate how the number of clusters affect coverage and the relationship between communication link count among UAVs and path loss thresholds. The study also compares the results with prior research, highlighting the impact of connectivity constraints on the required number of UAVs and the effective altitude of operation, addressing critical challenges in disaster scenarios and providing a foundation for future research in this area.

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