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Efficient deployment of UAVs for disaster management: A multi-criterion optimization approach

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ABSTRACT

Recently different information and communication technologies are investigated to manage disasters. Acknowledging disaster resilience, many efforts are commenced to monitor, forecast, and assess the situation in time. Response time and situational awareness is the key to save lives in disaster situations. These issues motivate the utilization of unmanned aerial vehicles (UAVs) in emergency conditions where a lack of communication and support services are core objectives to control. This paper has addressed UAV-assisted wireless networks' situational awareness deployment in disaster management as a mobile helping unit. In this regard, we have to efficiently place UAVs in emergency situations where infrastructure is devastated and diffused with features of minimum distance, cost, and number of UAVs. To this end, we optimize a multi-objective problem of UAV placement, users-UAV connectivity, distance, and cost. The formulated problem is a integer linear optimization problem (ILP). To solve it, we first propose a high complexity branch and bound (B&B) algorithm to find an optimal solution. Then, we develop a low complexity heuristic to conquer the objectives efficiently. Finally, simulation results show that our proposed approach can maximize the number of users with a minimum number of UAVs efficiently.

1. Introduction

Recently unmanned aerial vehicles (UAVs) are explored to improve wireless networks' performance, which leads to many applications including disaster management, surveillance, remote sensing, and delivery of goods [1,2]. UAVs' benefits vary from domestic usage (i.e., delivering food or parcel delivery at doorstep) to health services. UAVs can be implemented in the agriculture area for crop spraying, monitoring, irrigation, and fertilization. These services will help the farmers to assess the diseases of the crop in time and forecasting any disaster in real-time [3]. Health monitoring is another feature of UAV supported by the Internet of things (IoT). In this case, UAVs can collect data from users and stores it securely [4–6]. Moreover, spectrum enhancement along with interference mitigation is another feature which have contributed to advancement of UAVs in availing the resources of spectrum [7]. Similarly, UAVs can help in emergency conditions, i.e., assist disaster-affected people by providing wireless coverage, food, and medical aid (depending on the type of emergency held in the area). UAVs' inherent attributes in real-time data monitoring, adaptive height, line of sight (LoS) communication, and fast mobility have successfully implemented the aforementioned applications.

On-demand communication has significant importance in many fields, including military, festive, and disaster areas [8]. Centralized deployment and distributed motion control algorithms have been used to cope with the proper placement of UAVs. In the case of centralized deployment, the UAVs assist only those users which are previously known to the UAV. In contrast, in the case of on-demand communication, UAVs have their motion control strategy to provide on-demand coverage to users. In addition to the mentioned advantages, UAVs can also act as relays in the area where the base station suddenly stops working due to malfunction. This will help make communication between the unattended users and neighboring base stations connected to the malfunctioned base station [9].

1.1. Proposed disaster scenario's for implementation

UAVs can be deployed as mobile helping units in the case of disaster management. UAVs can provide network connection, medical, and food aid to users based on the type of disaster and user requirements. Fig. 1 shows four different kinds of scenarios. In the first scenario, a flood-affected area is considered with UAVs and users on the ground. A medical center and rescue department is providing aid and services in emergency conditions. The main city path has been cut down due to the flood; hence, a mobile helping unit-UAV can be deployed to provide services required by users in terms of network connection,

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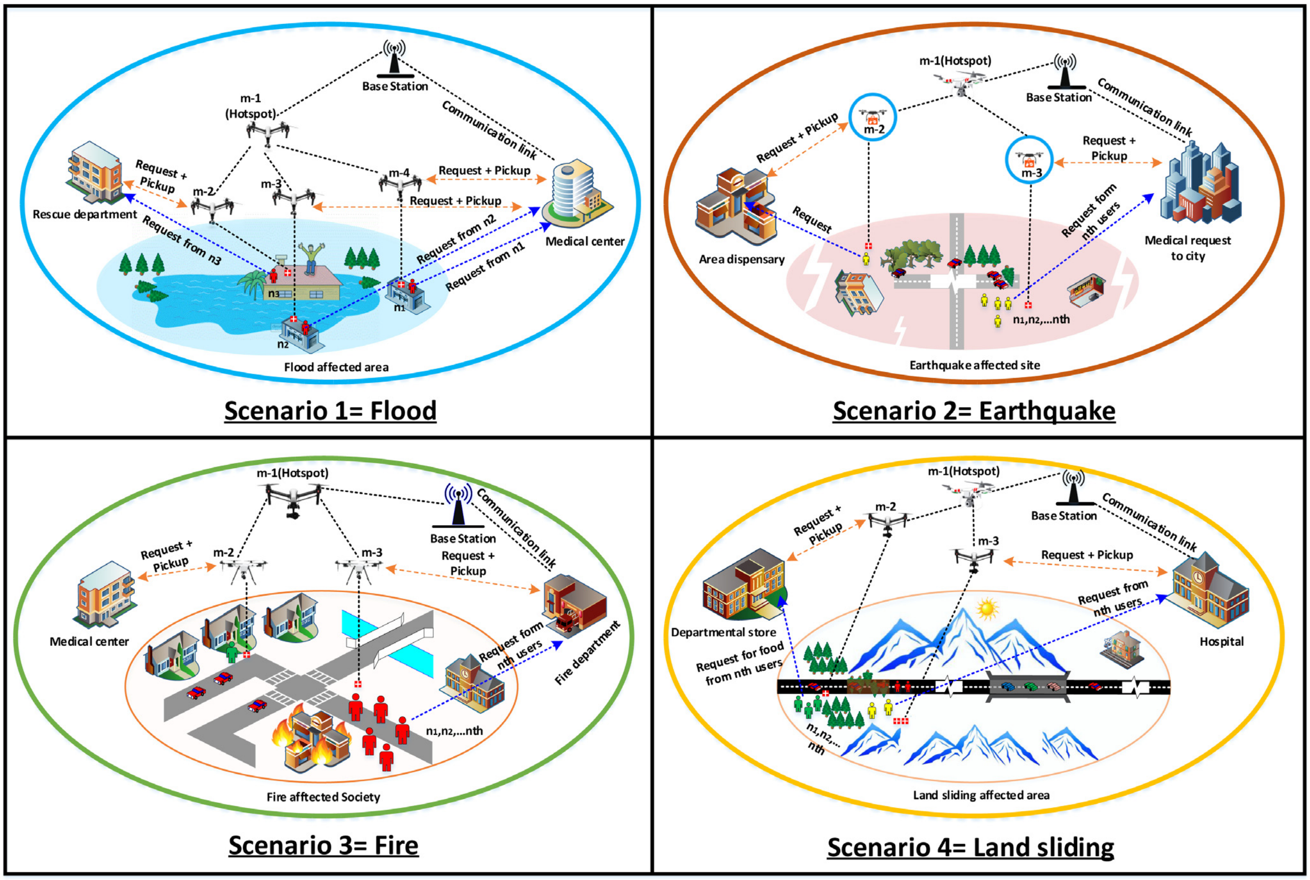


Fig. 1. Different scenarios of disaster management.

aid, and food. The second scenario depicts an earthquake situation where most medical services and humans found difficulty reaching as the roads are not fit to travel. Additionally, the network infrastructure may be damaged because of the earthquake. Here, UAV-based mobile helping units can provide network coverage and essential medical services. In the third scenario, an abrupt fire eruption occurs where MHU-UAVs can provide emergency medical services (oxygen, masks, and medicines) to the rescued persons finding difficulty breathing and getting injured during the fire escape. In the fourth scenario, we have taken landslide in hilly areas where icebergs melt in severe weather changes or thunderstorms. In this case, the traveling communication link roads vanish or got slide from the place. Tourists can get stuck in this place and get short of water and medical services, and food. UAV-based mobile helping units can assist in these disaster-affected areas.

1.2. Contributions

Situational awareness, fast communication links, and effective deployment of UAVs play a significant role in disaster situations; as maximum users, accommodation will help rescue more people from the disaster. Our target in this paper is to utilize a minimum number of UAVs and provide coverage to the maximum number of users while minimizing the cost and distance to maintain the overall system's efficiency. Following are the main contributions of this paper:

- **Modeling:** We contrived a novel framework for multi-objective ILP to assist disaster-affected users. The purpose of using ILP is making decisions in linear environment. Since, we are dealing with decisions whether to make connection or not, depending on scenario emergency; ILP found as an appropriate problem technique to be resolved. In particular, we have focused on cost-effective UAV deployment with maximum users to UAV connectivity disseminating to the minimum distance. The formalized model is subject to the following constraints; assures connectivity, the minimum number of users, and UAV deployment.
- **Algorithm:** To effectively place UAVs, we adopted (B&B) algorithm. We then propose a low complexity heuristic algorithm for the performance assessment of the proposed problem.
- **Validations:** Under various scenarios, B&B and heuristic results are taken, which demonstrates that the proposed heuristic algorithm attains comparable results as B&B algorithm with less complexity.

The rest of the paper is organized as follows: Section 2 provides an overview of related work. Section 3 presents the system model considered in this paper. Section 4 describes the mathematical formulation for UAV deployment and its solution using B&B and proposed heuristic algorithms. Section 4 presents simulation results for performance evaluation of proposed work. Section 6 provides concluding remarks.

2. Related work

Recently, there have been research efforts in the area of deployment of UAV-assisted networks, which are considered for several different applications, including disaster management.

2.1. Deployment of UAV-assisted wireless networks

The fast deployment of UAV networks for optimal wireless coverage is presented in [10]. The authors have proposed two optimization problems, i.e., minimization of maximum deployment delay and overall

Table 1
Overview of deployment, DM and UAVs joint venture of deployment and DM (UD = UAV deployment, DM = Disaster management, JDDM = Joint deployment and disaster management).

Ref.	UD	DM	JDDM	Remarks
[10]	✓			Optimal deployment of heterogeneous UAVs have done to provide coverage to target areas. A min–max and min-sum problem for delay have also been proposed.
[11]	✓			This paper have proposed a novel implementation method by introducing UAVs at different heights which resulted in searching of whole area in minimum period of time.
[12]	✓			Particle Swarm Optimization method have used for 3D placement and increased coverage. The authors have proved the effectiveness of proposed technique through stable performance and fast convergence.
[13]	✓			Greedy search algorithm is used to minimize the number of UAVs and increased the load balance. The authors have worked on discontinuous locations through an adaptive algorithm for optimal locations.
[14]	✓			Throughput of system in dynamic situation have increased through actor base deep reinforcement learning method. Simulation results have proved that throughput have controlled more as compared to previous heuristic techniques.
[15]	✓			This paper have proposed distributed poison method in 1D and 2D random user environment. Moreover, majority rule technique have been opted to drag UAV to user burdened environment.
[16]		✓		The authors have used UAV mounted base stations to provide services to portable hand or other devices in case of emergency.
[17]		✓		Multiobjective resource allocation scheme have introduced in heterogeneous IoT environment for surviving users stuck in disaster area.
[18]		✓		The authors have taken industrial scenario and used UAV in pre-disaster to minimize the accidents ratio. Moreover, future perspective to work in high risk environment have also discussed.
[19]		✓		Post disaster situation is controlled through rotary wing UAV, whose initial and final points are fixed to control battery timing of UAV.
[20]		✓		Swarm intelligence based localization and clustering schemes in UAV networks for communications in emergency situation is proposed.
[21]		✓		Radio resource optimization and trajectory is studied to provide critical information to vehicular networks in case of emergency.
[22]		✓		A two phase continuous approximation model is used to provide basic products to humans in disasters effected area through UAVs.
[23]		✓		The authors have used femto base station UAVs in real life scenario and hover UAV over a desired location to provide connectivity services.
[24]			✓	The authors have presented a novel idea of rescuing people to their nearest safe locations by providing a wireless connection through UAVs.
[25]			✓	Size of drone is made small in order to increase fly time of drones. The authors have provided life jackets through these newly invented drones but they face instability due to their miniature nature.
[26]			✓	A feasibility report have been presented for implementation of UAVs in different disaster scenarios recently occurred and the role of UAVs have been discussed for infrastructure monitoring and post disaster scenario.
[27]			✓	The idea of author is to replace conventional infrastructure system of wireless connection with UAVs. They have provide maximum throughput and fairness among users of flooded area.
[28]			✓	Researchers have used k-mean clustering selection and real time distributed techniques to provide coverage and maximize end to end sum rate in disaster area where network is not available due to network congestion.
[29]			✓	The authors have used three types of node, ground node, mobile nodes and aerial nodes which are declared as UAVs. Instead of using base stations they have used mobiles and ground nodes to provide coverage.
[30]			✓	An extensive theoretical research have done to provide in depth analysis of the demand and situation created in disaster scenario and how UAV can be deployed in such situation.
[31]			✓	The author have proposed Bee Colony Algorithm for deployment of UAVs in post disaster scenario and compared its result with previously existing genetic algorithm.
[32]			✓	A novel distributed algorithm technique, VESPA, have used to search locate and provide coverage and medical information from ground nodes and forward to base station.
[33]			✓	A three step mechanism, i.e., preparedness, assessment, response and recovery is introduced to invigilate and in time control on disaster issue.
Our contribution	✓	✓	✓	Branch and bound algorithm and a low complexity heuristic is proposed for joint UAV deployment and user association or Disaster Management.

delay. The deployment of UAV each time started from the same location and used a fully polynomial-time approximation scheme. In [11], battlefield software has been used to deploy UAV for targeting the aim. A comparison between existing techniques is provided to prove the effectiveness of the results. The authors have deployed UAVs at different heights in an area to minimize searching time. Particle swarm optimization is used in [12] for the 3D deployment of UAV to provide maximum coverage. The authors in [13] have maximized the load balance and minimize the number of UAVs by considering constraints on UAVs remain fixed to the base station and a robust backbone network should be formed. The problem is segregated into two parts to decrease the problem's complexity and solve it through a hybrid algorithm. UAV's real-time deployment is done in [14] to find optimal UAV positions and the maximum throughput of mobile users. The problem is the mixed-integer non-convex problem. The authors have solved through the actor-critic-based deep learning reinforcement method. The authors in [15] have used an adaptive approach to communicate with users through adaptive displacement and distance modeling. Non-real time monitoring is performed as it is challenging to optimize timely up-gradation of location.

2.2. UAV-assisted networks for disaster management

In [16], the authors have proposed UAVs in collaboration with the machine to machine communication in disaster scenarios by leveraging cellular networks. UAV mounted base station network access and resource allocation algorithm are used to increase human portable machine-type devices. Moreover, the transmission power for relaying is also minimized to improve the performance. Similarly, the authors in [17] have used the distributed non-orthogonal multiple access (NOMA) method for efficient deployment of UAV in the disaster scenario without successive interference cancellation (SIC). A multiobjective resource allocation problem is designed for survivors and IoT devices. The joint working of distributed SIC NOMA increased users' sum rate and access of devices to UAVs. In [18], the increasing risks in the industry due to the sudden failure of system and accidents is discussed. The authors have proposed deploying UAVs in pre-disaster scenarios to monitor the industrial system intelligently and curb the causes of accidents. Real case studies have also been discussed to show the results of the suggested system. The authors in [19] have served a post-disaster area with distributed users where an optimal path is selected, which can start and end the journey at the same location within a specified battery limit. The problem is expanded to a multi-armed bandit problem and solved by two path planning algorithms.

A technique based on UAV utilization with swarm intelligence-based localization and clustering schemes in disaster scenarios has been proposed in [20]. Both clustering and localization techniques are based on particle swarm optimization. The particle is used for search space in a given boundary, inter-cluster distance, intracluster distance, localization, and residual energy. The authors in [21] have deployed UAV in disaster scenario by jointly optimizing trajectory and radio resource management. The problem is NP-hard and hence resolved in the sequence of convex problems. Results have shown that UAVs adjust their velocities during the flight. The authors in [22] have studied optimum distribution locations and the services need to access these locations. The continuous approximation model has been used to calculate UAVs' speed, path, and trajectory in such scenarios. The problem is NP-hard type and non-linear. The authors in [23] have implanted femtocell base stations on UAV to provide coverage to the destroyed area. Their study and technique have proved that the number of UAVs can be decreased by increasing height or more advanced UAV type. Statistical results have also been given to validate the presented theory.

2.3. Joint deployment of UAVs and disaster management

The design and deployment of UAV-assisted for coverage and rescue operations for disaster management are presented in [24]. The authors have discussed multi-folded objectives. The first objective is to provide synchronization to maintain wireless coverage, while the second gathered information and provide it to rescue units. The third is the robust configuration of UAV, i.e., in connection disruption, no UAV should break the chain. Fourth is an alert system for affected people, i.e., telling them which place of rescue is close to them and how they can avail of continuous network coverage. The fifth is the utilization of available mobile services to cope with the shortage of wireless signals. UAVs can be used from simple photography in events to image clicking for disaster scenarios. These images can help to locate people who got stuck helplessly in catastrophic conditions. A rescue mission UAV is developed in [25], which can carry payload. This type of UAV can be deployed for the delivery of items in the case of an emergency. A trade-off between flight time and weight is studied for a given battery. The authors in [26] have reviewed the integration and application of UAVs in disaster and post-disaster scenarios. The authors have studied previous disasters and proposed the implementation of UAVs in different stages of the disaster. UAVs can be used to measure the magnitude of damage caused to the area. Moreover, image acquisition of the disaster site can also help in the assessment of the damage.

In [27], the maximum coverage is optimized to maximize the user throughput by assuming a flood scenario in San Francisco. The authors have provided fairness among different geographical locations. The authors in [28] have used UAV as a relay in an emergency where infrastructure is destructed or communication is lost due to heavy load conditions. K-means clustering method is used for efficient allocation of users. Moreover, the authors have also used a distributed real-time resource allocation scheme and embedded programming to increase end-to-end sum-rate and fast network recovery in a disaster. The authors in [29] have used the concept of nodes. Three types of nodes have been used: stationary, ground, and aerial nodes. The architecture is deployed so that no Internet and the cellular base station is required for communication in disaster scenarios. Wireless sensor networks and UAVs are collaboratively implemented to control disaster management in [30]. In [31], the authors have proposed an artificial bee colony algorithm for successful UAV deployment in a post-disaster scenario. This algorithm will help in finding the optimal height and network throughput of the model. The artificial bee colony algorithm is then compared to other genetic algorithm and implemented in a post-disaster situation. Results have shown that coverage and network throughput will be enhanced. An application is also developed at the user end to support situational awareness. VESPA, a distributed algorithm, is used in [32] to self organize the disaster affected persons. The authors have monitored the effected area with flying UAVs. UAVs' purpose is to search and locate the area where communication is a problem and provide medical and information services. In addition to the reviewed literature, the authors in [33] have used a three-step mechanism for successful deployment of the multi-UAV system, i.e., prevention, preparedness, response, and recovery. According to the authors, the suggested steps will help in localizing and rescuing disaster-affected persons.

Table 1 provides a summary of related work. Compared to previous work, we have proposed UAVs as mobile helping units to assist users with medical, food aid, and network coverage. The novelty of work is the deployment of UAVs with constraints on cost, distance, and connectivity.

3. System model and problem formulation

In this section, we will elaborate the variable types used in mathematical model. Then, the type of channel model utilized between user and UAV, i.e., channel model which will be further utilized in formulation of our desired problem. Fig. 2 shows a UAV-assisted wireless network environment considered in this paper, which consists of M number of UAVs and N number of users in the network. Let L be the number of potential locations for the deployment of UAVs. The goal is to provide connectivity to users at minimum cost and minimum distance. The presence of mth UAV at lth location can be represented by a binary variable x_m given as:

$$x_m = \begin{cases} 1, & \text{if UAV is placed at } lth \text{ location} \\ 0, & \text{otherwise.} \end{cases}$$

On the other hand, y_{mn} denotes UAV connectivity with users and can be written as:

$$y_{mn} = \begin{cases} 1, & \text{If } mth \text{ UAV is connected to } nth \text{ user} \\ 0, & \text{otherwise.} \end{cases}$$

Moreover, β is the percentage of users who need to be connected. At the same time, γ_{max} and γ_{min} are considered as maximum and minimum possible connections of a user to UAV. In other words, we constrained our system to have at least one possible connection between the user and the UAV. Another parameter cost is used in our objective function, which is defined as c_m for a single UAV, and C^{max} describes all UAVs' overall maximum cost. Distance between user and UAV is taken as d_{mn} and d^{max} is the maximum distance between user and UAV.

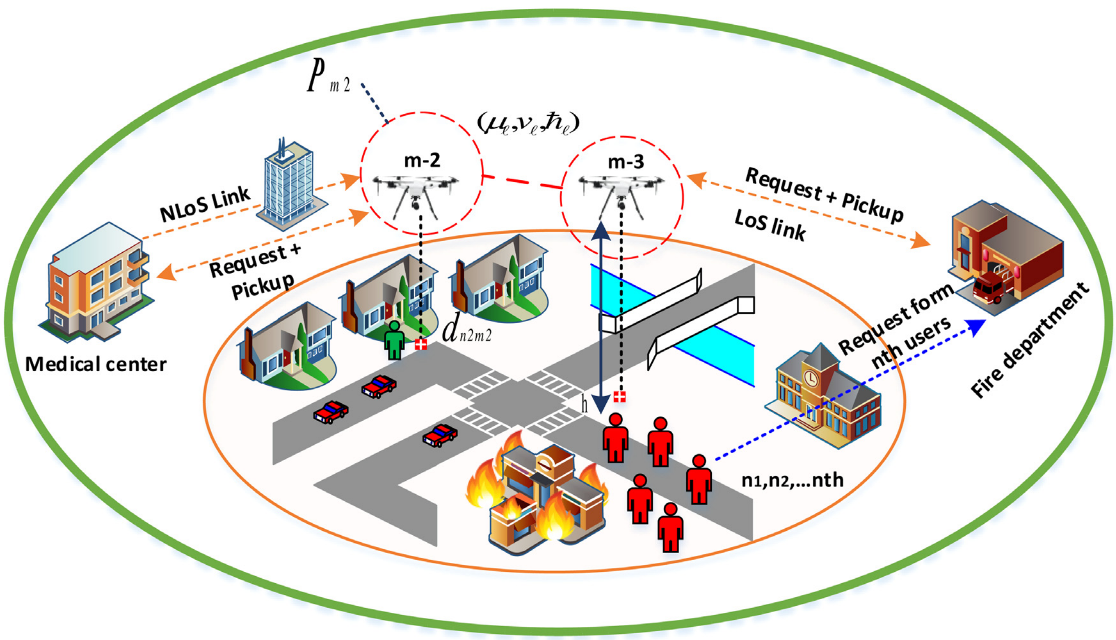


Fig. 2. AG channel model for used scenarios.

3.1. Channel modeling

Task completion in our described scenarios is done in a location-aware environment. For simplicity, we have taken three potential locations of users in each scenario, where we need to provide the facilities through UAVs. The location of users can be denoted by ℓ. UAVs are implemented in a $3D$ coordinate system as UAVs are flying devices; therefore, UAVs have the height to monitor. UAVs height is of great importance in its placement as:

$$Height \propto \frac{Coverage}{Signal\,Strength}.$$

The relationship shows that UAVs have better coverage at higher altitudes and low signal strength is lower, while at lower altitudes, signal strength is good, but coverage is affected. Since we provide services only in terms of the parcel, we have fixed UAVs' height as $\hbar$. Potential location of UAV at height $\hbar$ is represented as μ_ℓ and ν_ℓ. Hence, UAVs location and height can be represented in 3D cartesian system, as $(\mu_\ell, \nu_\ell, \hbar_\ell)$. UAVs are moveable vehicles, their location can vary from $(0, 0, \hbar)$ to $(\mu_{max}, \nu_{max}, \hbar_{max})$. The channel model for our system is depicted in Fig. 2 where UAV's height, coordinate, and distance is clearly showing. In the given scenario, we have air to ground (AG) path loss model, which will be discussed below.

AG path loss model

Let P_{LoS}^{mn} be the probability of path loss of LoS communication between *mth* UAV and *nth* user, then probability will be given as:

$$P_{LoS}^{mn} = (1 + p\exp(-q(\phi_{mn} - \delta)))^{-1} \quad \forall m, n, \tag{1}$$

where p and q are constants and their values depend on the environment (urban, suburban, and rural) and the signal's carrier frequency. δ is the path loss-exponent. While the elevation angle between UAV flying at height h and user present at the ground station is given by:

$$\phi_{mn} = \tan^{-1}\frac{h}{d_{mn}} \tag{2}$$

where d_{mn} is the distance between *mth* UAV and *nth* user and can be calculated as:

$$d_{mn} = \sqrt{(\mu_m - \mu_n)^2 + (\nu_m - \nu_n)^2 + h^2} \quad \forall m, n, \tag{3}$$

where μ_m, μ_n are the x-axis coordinate of UAV and user at mth and nth location and ν_m, ν_n are the y-axis coordinate of UAV and user at mth and nth location.

As, we kept the height constant, i.e., $h = 0$, Therefore, Eq. (3) can re-write as:

$$d_{mn} = \sqrt{(\mu_m - \mu_n)^2 + (\nu_m - \nu_n)^2} \quad \forall m, n. \tag{4}$$

Further, for calculating path loss with LoS and non-line of sight (NLoS), we will use δ, carrier frequency denoted as 'f_c' and radius of cell denoted as r_{mn}. According to the AG model, LoS and NLoS can be written as:

$$L_{Los,mn} = Z + \lambda_{LoS} \quad \forall m, n, \tag{5}$$

$$L_{NLos,mn} = Z + \lambda_{NLoS} \quad \forall m, n, \tag{6}$$

where $Z = 10\delta log(\frac{4\pi f_c r_{mn}}{\upsilon})$, υ is the speed of light and λ are random losses that will occur in addition to free space loss and depends on environmental conditions. If G_{mn} is the channel gain for the given system, then after utilizing Eqs. (5) and (6), channel gain will be written as:

$$G_{mn} = (Z + P_{LoS}^{mn}(\lambda_{LoS} - \lambda_{NLoS}) + \lambda_{NLoS})^{-1} \forall m, n \tag{7}$$

where λ_{LoS}, λ_{NLoS} are the LoS and NLos loss of medium.

Signal to noise ratio (SINR) for the given channel is calculated as follow:

$$SINR_{mn} = \frac{P_m G_{mn}}{\sum_{i \epsilon I_{noise}} P_i G_{in} + \lambda^2}, \tag{8}$$

where P_m is the downlink power of UAV. $i \, \epsilon \, I_{noise}$ is noise from other UAVs and BS. λ is random noise. P_i is the power of interfering UAVs and BS.

3.2. Problem formulation

Considering Fig. 1, we have mathematically formulated the problem of UAV placement and its connection to the users with cost and distance. The joint optimization problem consists of minimizing the number of UAVs, maximizing the number of user UAV connections, distance minimization between user and UAV, and minimizing UAV cost. The optimization problem is formulated as:

$$\min_{\substack{x_m,y_{mn}\\ \forall n,m}} \left\{ \frac{\sum_{m=1}^{M} x_m}{M}; \frac{-\sum_{n=1}^{N}\sum_{m=1}^{M} y_{mn}}{N} \right. \\ \left. \frac{\sum_{n=1}^{N}\sum_{m=1}^{M} y_{mn} d_{mn}}{N d^{max}}; \frac{\sum_{m=1}^{M} x_m C_m}{M C^{max}} \right\}$$

Subject to;

$$\begin{aligned}
&C1: \sum_{n=1}^{N}\sum_{m=1}^{M} y_{mn} \geq \beta N \\
&C2: y_{mn} \leq x_m,\ \forall n,m \\
&C3: \sum_{n=1}^{N} y_{mn} \leq \gamma^{max} x_m\ \forall m \\
&C4: \sum_{n=1}^{N} y_{mn} \geq \gamma^{min} x_m\ \forall m \\
&C5: \sum_{m=1}^{M} y_{mn} \leq 1,\ \forall n \\
&C6: y_{mn} \leq \max(0, d^{max} - d_{nm}) \forall m,n \\
&C7: \sum_{m=1}^{M} c_m x_m \leq C^{max} \\
&C8: x_m \in \{0,1\}, y_{mn} \in \{0,1\}\ \forall m
\end{aligned} \tag{9}$$

The problem in (9) is an ILP that maximizes the users' connectivity while considering the minimum number of UAVs. The optimization problem is formulated considering practical constraints. C1 limits the minimum number of users that need to be accompanied by a single UAV. This constraint will helps in maintaining minimum threshold users-UAV connection level to assure the connectivity. Since, we are dealing with disaster scenario, connectivity of users to UAVs are of prime importance. Moreover, no UAV will be left unused through this constraint. C2 is the connectivity constraint of the deployed UAV to the user. It states that if a UAV is deployed at a certain place m, i.e., $x_m = 1$, the user may be connected to it or not. However, if $x_m = 0$, then no user can be connected to that location which means a UAV placement is made necessary for reliability of the proposed system. The constraints C3 and C4 enforces that there is a limit on maximum and minimum numbers of user connections allowed to be connected to a UAV. This will help in maintaining a uniform behavior, i.e., no UAV will get over-burdened and under-burdened. The constraint C5 ensures users' assignment to UAV that at a time, one user can connect to one UAV. No user is allowed to connect to multiple UAVs. Where d_{mn} is the distance between user and UAV, which will be kept minimal to maintain a good connection. C6 restricts the system that no UAV and user can cross the given maximum distance d^{max}. c_m is the cost of a single UAV that is selected for performing the delivery operation. C^{max} is the maximum cost for all UAVs. C7 restricted that overall UAV's cost will not exceed C^{max}. Hence, by minimizing the system's overall cost, maximum user UAV connection will be built up. According to constraint C8, vector and matrix should vary between 0 and 1.

In the following sections, i.e., Sections 4 and 5, we will discuss about B&B algorithm and low complexity heuristic proposed for the solving the designed mathematical model. Then, detailed simulations have done to give the optimality of results.

4. Proposed solutions

Efficient deployment of UAV is necessary as it helps in minimizing the cost of the overall system. UAVs are deployed in a given scenario so that no user can use more than one UAV, and cell-edge users are dealt with efficiently. Moreover, the distance between the user and UAV is also minimized for efficient connection building. In this paper, we tried to optimize the results through two approaches. First, the B&B algorithm is used to solve integer problem and RSS heuristic proposed in Algorithm 2. Then, a low complexity heuristic is proposed in Algorithm 3.

Algorithm 1 Branch and bound algorithm for UAV deployment, user connectivity, cost, and distance minimization.

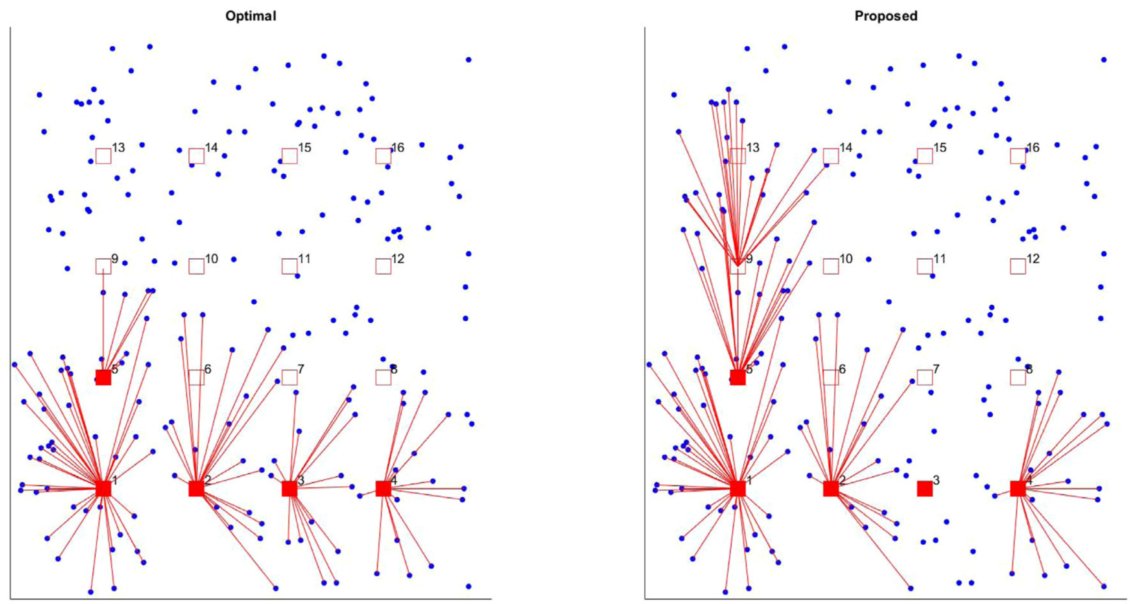
Inputs: N , M , $Beta$, γ_{max} , γ_{min} , C_{max} , d_{min} , d_{max}
Initialization:
$O_0 \leftarrow Optimization\ Problem$
$N \leftarrow \{O_0\}, set\ of\ active\ nodes$
$\lambda \leftarrow \infty$, $objective\ function\ value\ for\ incumbent\ solution$
$S^* \leftarrow \Phi$
$S \leftarrow \phi$, $current\ solution$
$k \leftarrow$ $number\ of\ subproblems\ for\ each\ node$
while $N \neq \phi$ **do**
  $W \leftarrow select(N)$
  $W \leftarrow N \setminus w$
  $Q \leftarrow split(W,k)$
  for $j \in \{1,\dots,k\}$ **do**
    $[S,\lambda] \leftarrow$ solve_ILP$(O_j \in O)$
    if S $is\ complete$ **then**
      if $\lambda < \lambda^*$ **then**
        $S^* \leftarrow S, \lambda \leftarrow \lambda^*$
      end if
    end if
    if $\lambda < \lambda^*$ **then**
      $[S_2,\lambda_2] \leftarrow$ RSS$(S \in S^*)$
      if S_2 $is\ complete$ **then**
        if $\lambda_2 < (1-\epsilon)\lambda^*$ **then**
          $S^* \leftarrow S_2, \lambda^* \leftarrow \lambda_2$
        end if
      else
        if $\lambda_2 < \lambda^*$ **then**
          $N \leftarrow S_2$
        end if
      end if
    end if
  end for
end while

Table 2
Notations for Algorithm 1.

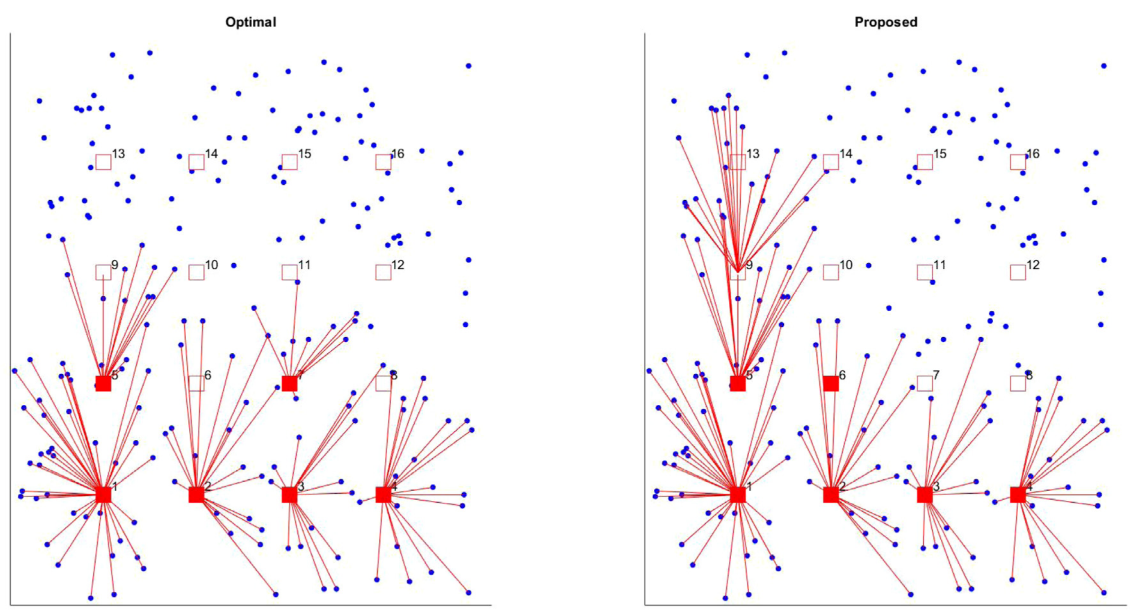
O_0	Root node of optimization problem in B&B
N	Set of active nodes
k	Number of sub problems of current node
W	Selected node
$S(S^*)$	Current (incumbent) solution
$\lambda(\lambda^*)$	Score of current (incumbent) solution
split(W,n)	Split problem into n subprobems
$solve\_ILP(O_j \in O)$	Solve ILP for problem O_j
$S^* \oplus S$	Find indexes of all integer variables that have same value in S and S^*

4.1. B&B with RSS algorithm

B&B algorithm is used for solving combinatorial optimization problems. These problems have exponential growth in time and explore all the possible solutions. Then, the branch is checked against the upper and lower bounds of the solution. If the divided branch cannot find a better solution than the previously best solution, then the branch is discarded [34]. B&B to solve the problem mention in (3.2). This algorithm aims to break the whole problem into small subproblems until the required result is achieved. Table 2 is giving a brief overview of the notations used in the pseudo-code. Algorithm 1 is initialized



(a) β=0.5



(b) β=0.6

Fig. 3. Connections of users and UAVs for optimal and proposed for (a) $\beta = 0.5$ and (b) $\beta = 0.6$.

with basic network parameters; M, N, Beta, $\gamma_{max}, \gamma_{min}, C_{max}, d_{min}, d_{max}$. As B&B problems work in tree form. The main problem acts as the tree's root node and is divided into further sub-nodes that are active nodes. The set S is a container for all active nodes, while the main problem will continue to act as the root node. This criteria of node activation will continue until all nodes are conquered. Once the algorithm starts working, it will not stop until loop criteria is met or some terminating command is used. In each iteration, one subproblem, i.e., node is extracted from the set and further portioned into smaller subproblems (i.e., the number of objectives)—the problem 3.2 for ILP. An integer relaxation value is then applied to each subproblem to get the current solution S and its objective function value λ. In case we get a better solution compared to the incumbent solution. S^* is replaced by S, and λ^* is replaced by λ. Algorithm 2 is applied if the desired result is not found. RSS algorithm found all the indexes which have the same values in S and S^*. In step 21, the same values issue is fixed. Then, integer relaxation is solved on the remaining variables and replaced the previous solution by λ_2 and S_2. In step 23 to 27, a cutoff value obtained from RSS is set on the objective function. If a better value is obtained, then the incumbent solution is replaced by a new value; otherwise, non-integer values will be processed in the next iteration.

4.2. Heuristic solution for user-UAV distance and connectivity

Worst-case complexity poses a challenge to the B&B algorithm due to its exponential growth in network size. Hence, a low complexity heuristic is proposed to minimize the distance and connectivity objective jointly. Algorithm 3 shows the main execution steps for the

Algorithm 2 RSS subroutine

Inputs: S , S^*
Initialization:
$I \leftarrow S^* \oplus S$
$S \leftarrow Fix(S(I))$
$[S_2, \lambda_2] \leftarrow Solve\_ILP(S)$

heuristic algorithm. In first step, the algorithm is given with basic network parameters inputs N,M, $d_{max}, C_{max}\gamma_{max}$. We considered a grid for UAVs deployment with randomly distributed users and $N \times M$ connectivity matrix. In 2–4 steps, *for loop* for N users is run. The minimum distance for each user will be found and stored in Y. Then, proceeding to steps 6–19, *for loop* for M UAVs will run. This will check minimum and maximum users and UAVs deployment constraints. It will then terminate all those connections of users and UAVs that are less than the minimum required connections or greater than the maximum connections constraint. For steps 20–22, UAV connectivity constraint will be checked. In step 23, the weighted utility is being calculated.

Algorithm 3 Low complexity heuristic for user UAV connectivity distance and deployment cost.

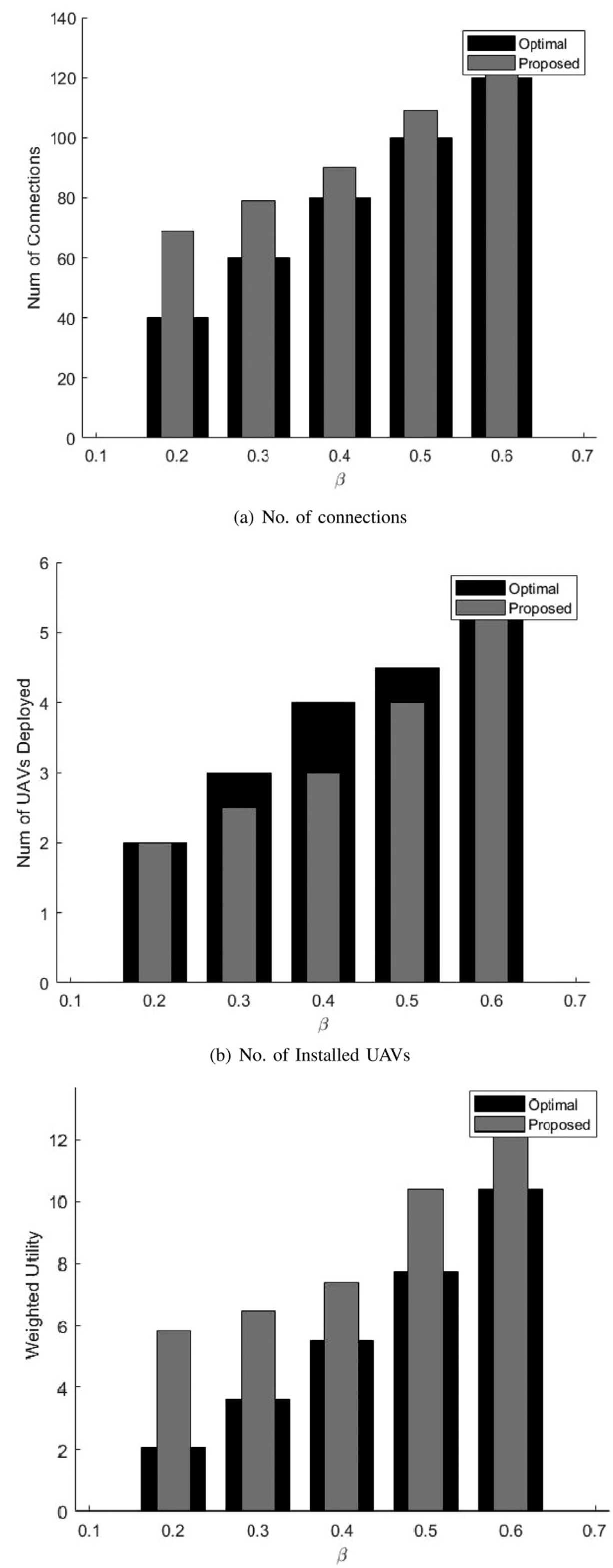
1: **Inputs:** N , M , γ^{max} , d_{max}, C_{max} **Initialization:**
2: **for** $n \in \{1, 2, \ldots, N\}$ **do**
3: $j \leftarrow \text{argmin}\ Y_{:,n}$
4: **Yj,n** $\leftarrow 1$
5: **end for**
6: **for** $m = 1 : M$ **do**
7: $e \leftarrow t - \gamma max$
8: **if** $t > 0$ **then**
9: **for** $i = 1 : e$ **do**
10: $k \Leftarrow argmaxU_{m,:}$
11: $U_{m,k \leftarrow 0}$
12: $T_{m,k \leftarrow 0}$
13: **if** $t < 0$ **then**
14: $U_{m,:=0}$
15: $T_{m,:=0}$
16: **end if**
17: **end for**
18: **end if**
19: **end for**
20: **for** $m = 1 : M$ **do**
21: $x_j \leftarrow (\sum$ **Yj,:** $> 0)$
22: **end for**
23: $f \leftarrow f_1 + (-f_2) + f_3 + f_4$
24: Outputs y_{mn} , x_m , f

4.3. Complexity analysis

Complexity analysis makes a comparison between B&B and the proposed heuristic. The reduced complexity of heuristic can be calculated in number of flops [35]. Complexity convolution in algorithm 3 for line (4–7) is N(M+1) flops while for lines (8–21) is M(3N + NM + 2). The worst-case complexity of line (22–24) is M(N + 1). The number of flops for the line (25) is (M + MN + 3). The overall complexity is given as:

$$\begin{aligned} No.of\,flops &\approx N(M+1) + M(3N + NM + 2) \qquad (10) \\ &+ M(N+1) + (M + MN + 3) \\ &\approx O(M^2 + 6MN + 4M + N + 3). \\ &\approx O(M^2 + MN) \qquad (11) \end{aligned}$$

(11) is the polynomial time complexity of proposed heuristic with users and UAV location while the worst case complexity of B&B algorithm is $O(2^{M^2 N})$. A comparison in term of number of flops between proposed and B&B algorithm is calculated in Table 3.



(a) No. of connections

(b) No. of Installed UAVs

(c) Utility

Fig. 4. Comparison of proposed algorithm with optimal (a) number of connections versus β, (b) number of UAVs deployed versus β, and (c) weighted utility versus β.

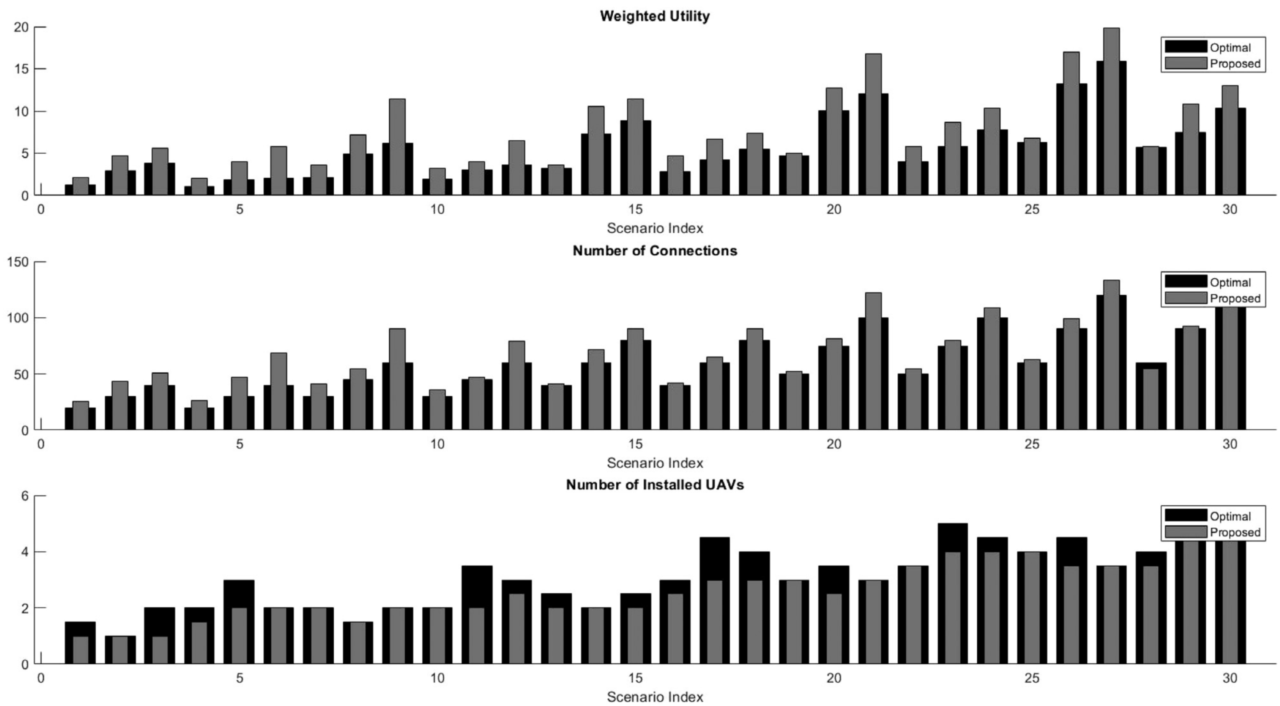


Fig. 5. Multiple objectives of UAVs for different scenario indexes.

Table 3
Complexity in number of flops.

Scenarios	M (Network grids)	N	Optimal	Proposed
1	3 × 3	50	2^{450}	159
1	3 × 3	100	2^{900}	309
2	3 × 3	150	2^{1350}	459
3	3 × 3	200	2^{1800}	609
4	4 × 4	50	2^{800}	216
5	4 × 4	100	2^{1600}	416
6	4 × 4	150	2^{2400}	616
7	4 × 4	200	2^{3200}	816
8	5 × 5	50	2^{1250}	275
9	5 × 5	100	2^{2500}	525
10	5 × 5	150	2^{3750}	775
11	5 × 5	200	2^{5000}	1025

5. Performance analysis

In this section, we compare the performance of the B&B algorithm with RSS heuristic is compared with low complexity heuristic for the efficient deployment of UAVs. We considered a scenario where M UAVs are deployed for $N = 50-200$ number of users. The users are uniformly distributed while a grid of M×M, i.e., 3×3, 4×4, 5×5 is considered for M discrete locations of UAVs. The value of beta, which is the minimum connections that need to be followed as discussed in problem (9) is taken as $\beta = (0.2-0.6)$. Following constraint C4 and C5 in problem (9), the value of G_{min} and G_{max} is kept at 10 and 200 to put a lower and upper bound on minimum and maximum user UAV connections. The goal of this paper is to minimize the utility function given in the form of weighted sum function as:

$$f = min(\alpha_1 f_1 - \alpha_2 f_2 + \alpha_3 f_3 + \alpha_4 f_4) \tag{12}$$

where f_1 represents the first objective function, which attempts to minimize the number of UAVs. f_2 represents the number of connected users to UAV, which is the second objective function. The third objective is to minimize the distance between the user and UAV, while the fourth goal is to minimize UAV placement's overall cost. $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ are the individual weights assigned to each function. All the objectives have assigned equal priority, i.e., $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = 0.25$.

Figs. 3(a) and 3(b) is showing connection between users and UAVs at $\beta = 0.5$ and $\beta = 0.6$. It can be seen that a low number of users are accompanied by UAV at $\beta = 0.5$ while a large number of users are accompanied by $\beta = 0.6$. This is because UAVs are deployed in 3 × 3 and 4 × 4 grid structure apart from beta value. When we raise the percentage of users' connectivity to UAV, i.e., β more users get a chance to connect to its nearest UAV since more UAVs are already deployed in the grid with potential locations. Therefore, the objective function values increased on the increased value of β and decreased on the low value of beta following constraint C1 from problem (9). If a UAV is underutilized; not following C1 constraint, UAV will be removed to minimize the cost of system.

Fig. 4(a) is presenting results in term of users connections at range of $\beta = (0.2-0.6)$. It can be seen that number of connections utilization increased with an increased value of β. At $\beta = 0.2$, almost 40 users successfully make connections in optimal while the proposed algorithm succeeds with 65. While at $\beta = 0.5$, the proposed is getting 115 connections and optimal is getting 100 connections, i.e., optimal is competing with proposed algorithm with a minor difference. Similarly, it can be seen that the connections difference between both algorithms decreases as the value of β gets larger. Similarly, Fig. 4(b) is depicting the utilization of UAVs in pursuing connections. UAVs deployment for both algorithms is the same except at intermediate points. The optimal and proposed algorithm is competing with each other. Fig. 4(c) demonstrates the utility function between connection and deployment of UAVs. Here, utility function is demonstration between users connections and installed UAV for a range of β. It can be clearly seen that at lower values of β, the proposed algorithm is competing for more to optimal while the margin tends to minimize its difference at ascending values. The cumulative performance results for a range of given β for users connection and potential UAV deployment in the grid is shown in Fig. 5. The weighted utility function is divided into sets of β values taken in our simulations. The function is divided in set of scenarios where each scenario represents a range of given β, users and number of UAVs installed. The same depiction is representing the competing number of UAVs and the number of users utilization collectively in both algorithms. However, the proposed algorithm gives better results than optimal, since it deploys maximum UAVs to maintain maximum user connectivity.

6. Conclusion

In this paper, we have investigated a UAV-assisted disaster scenario in which multiple emergency situations are taken to emphasize on the importance of installation of UAV in catastrophic environment. We used ILP to model our objectives and set of constraints. Our optimization problem is formalized to maximize the number of connections between users and UAV while guaranteeing the least user connectivity. The problem is extended to generate an effective deployment solution with cost and distance. Our problem is solved through the B&B algorithm to optimize the results. To demonstrate the effectiveness of the proposed problem, we have also proposed a low complexity heuristic. From the simulation results of both B&B and heuristic, the maximum connection between users and UAVs are maintained through the minimum deployment of UAVs. The results are shown at different values of β, which concludes that B&B and heuristic compete with each other in user connections, UAV deployment, and weighted utility. A future extension of this work could be data offloading and multi-layer UAVs installation.

CRediT authorship contribution statement

Rooha Masroor: Conception and design of study, Acquisition of data, Analysis and/or interpretation of data, Writing - original draft. **Muhammad Naeem:** Conception and design of study, Analysis and/or interpretation of data, Writing - original draft. **Waleed Ejaz:** Conception and design of study, Analysis and/or interpretation of data, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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All authors approved the version of the manuscript to be published.

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