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Article

Intelligent UAV Deployment for a Disaster Resilient Wireless Network

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Abstract: Deployment of unmanned aerial vehicles (UAVs) as aerial base stations (ABSs) has been considered to be a feasible solution to provide network coverage in scenarios where the conventional terrestrial network is overloaded or inaccessible due to an emergency situation. This article studies the problem of optimal placement of the UAVs as ABSs to enable network connectivity to the users in a coverage free zone. The main contributions of this work include two approaches to position the UAVs and to assign user equipment (UE) to each UAV, such that the sum-rate and the coverage probability of the network is maximized. An approach can be selected depending on the prevailing scenario. The first approach uses clustering algorithm to determine the 2D positioning of the UAV and a matching algorithm is used for UE assignment by considering the characteristics of the air-to-ground propagation channels as well as the impact of co-channel interference from ABSs. Then it uses exhaustive search on different altitudes to find the optimal altitude. In the second approach, 2D positioning and UE assignment are done similarly to the first approach. However, the sub-optimal altitude is estimated using particle swarm optimization (PSO). The first approach is suitable for a system which has computational resource constraints or lower probability of line of sight (LoS) links. In contrast, the second approach is suitable for data rate greedy systems or a higher probability of LoS links.

Keywords: Aerial base station, average spectral efficiency, interference mitigation, particle swarm optimization and unmanned aerial vehicles.

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1. Introduction

Conventionally, unmanned aerial vehicles (UAVs) have various applications in fields such as military, disaster management, search and rescue, security, photography, etc.[1]. The continuous improvements in the flight time endurance, the payload capacity, and other aspects have paved the way to applications of UAVs in fields such as agriculture, transportation, surveying, and most recently, in wireless communications. There main use cases of UAVs in wireless communications have been identified. A UAV may be used as an aerial base station (ABS), an aerial relay or an aerial mobile station (MS). Out of the three use cases, deploying UAVs as ABSs to enhance the coverage and capacity of terrestrial wireless systems, has attracted significant research attention. Specially, in circumstance such as special events, traffic offloading and natural disasters[2], [3]. High mobility, quick deployment capability and low capital expenditure of UAV ABSs make it an effective solution in above scenarios [1]. Furthermore, UAV ABSs increase the probability of line of sight (LoS) links, which enhance the

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received signal quality compared to non-line of sight (NLoS) links available in terrestrial base station (BS) networks.

The advantages of UAV ABSs come with some technical challenges, i.e, high mobility will demand complex control mechanisms[1], trajectory planning and wireless backhauling [4], on-demand deployment requires self-organizing network (SON) capability [5] and having LoS links increase the co-channel interference (CCI). Therefore, significant research attention has been focused on intelligent planning of UAV networks to overcome the challenges involved. The recent works of UAV deployment are focused towards three general areas [6]. The first area is revolving around the network structure of the UAVs, considering the network coverage utility [7] -[11], quality of the connectivity [12], [13] and the topology of the network [14]. The second area mainly focuses on deploying UAVs to cover targeted objects [15]. The third area focuses on using the UAVs as BSs to serve the UEs. In the third category, generally, all the UAVs are connected to each other and to a central control station [6],[17]. As it mentioned above, in order to gain maximum out of UAV BS, it should rely upon a complex control mechanism. The control mechanism can be a centralized algorithm where all the control decision are take from a global perspective [4],[7],[8],[18]-[28] or it can be a completely distributed or decentralized algorithm where each and every component take decision on its own in a fully autonomous manner [11],[29]-[39]. Centralized algorithms are capable of providing accurate decisions compared to decentralized approaches. However, to take accurate decisions, global information must be available at the central controller. This will add significant overhead and delay to the system, making it unsuitable in an on demand deployment scenario. In contrast, distributed algorithms share no information and make decision through some intelligent approaches and locally available data, resulting in lower overhead and delay in the system. However, as distributed algorithms completely rely on device intelligence and local information, limitations of device intelligence and inaccurate information may cause system failure as the core system does not have any control over UAV ABSs. Considering the above mentioned drawbacks, deploying an algorithm which is neither fully centralized nor fully distributed would be an effective solution. Therefore, in our work we are proposing an algorithm which is distributed and yet still share critical information in order to prevent sudden degradation of the system.

The control algorithm should focus on several aspects to ensure proper functioning of the system,namely, radio resource management, interference management, channel estimation and prediction, placement, user association, and trajectory planning. In [7], a multi-UAV deployment scenario is analyzed to maximize the coverage area, while minimizing the interference using circle package theory. An inverse approach is studied in [5] where UE projects an area of interest over the UAV swarm, and pick their preferences to maximize the coverage probability. Energy efficiency also a critical requirement as restricted power supply affecting the flight time endurance. There are several techniques introduced to compensate this requirement. such as radio frequency energy harvesting, wireless power transfer [40], simultaneous information and power transfer, self-interference exploitation [41], and etc. Furthermore, there are algorithmic approaches [8] which analyzes the deployment problem to increase the energy efficiency without loosing the quality of service(QoS) requirements. In [42], a UAV ABS scheme is proposed to assist the ground base stations (GBSs) to support increasing user density of a given area. A similar cooperative ABS - GBS scheme is analyzed in [3], which enables the user equipment (UEs) to cooperatively communicate with ABS and GBS. Additionally, Considering delay sensitive application, in [4], a ABS-GBS cooperative approach is proposed where it utilizes the diverse properties of ABS and GBS to cooperatively serve delay sensitive and general users. An ultra dense cloud drone network is proposed in [43] to provide flexible on-demand deployment of ABSs.

Comparatively, machine learning (ML) based deployment approaches helps for quick responses and to reduce data overheads. In [44], genetic algorithm and reinforcement learning is used for optimal deployment and user assignment. Notably, in terms of learning based deployment, a significant contribution is made in [16]. Where matching, clustering algorithm along with game theory is used

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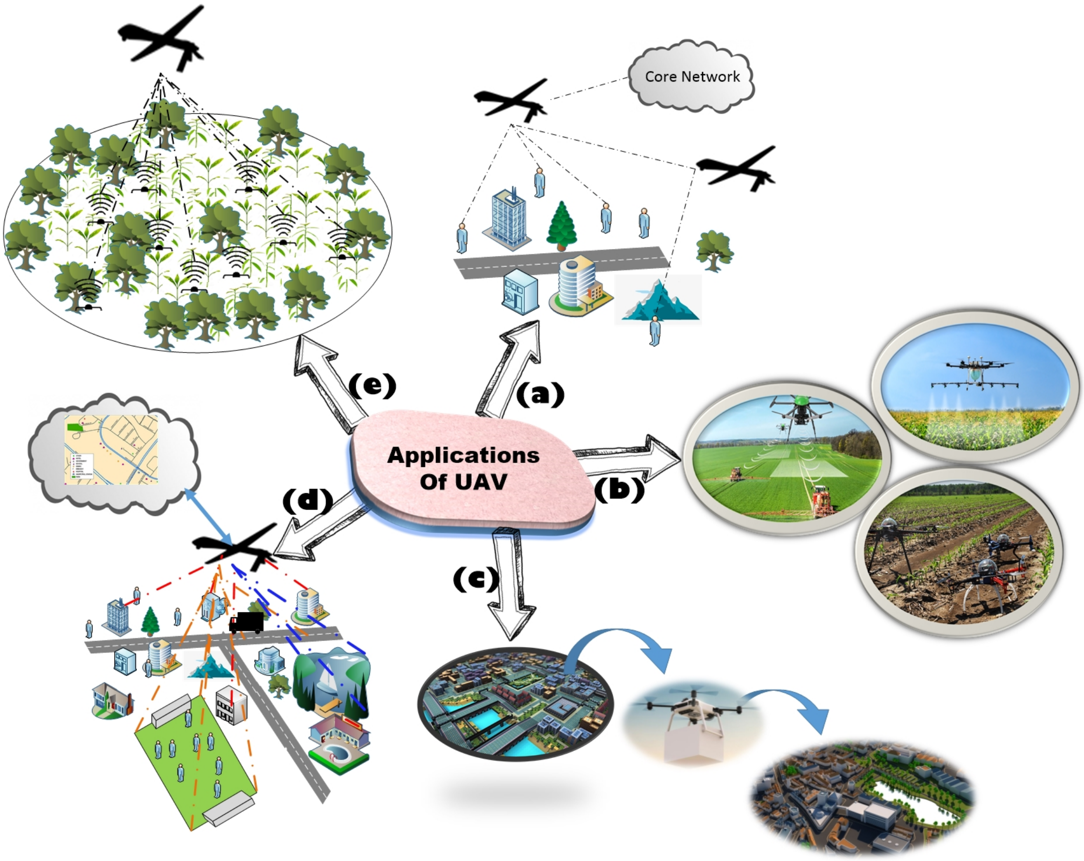

Figure 1. Application of UAV for a smart environment- (a)- communication, (b)- agriculture, (c)-Transportation (delivery), (d)- Surveying, (e)- data dissemination

to obtain optimal user assignment, 2D coordinates and altitude to maximize the sum-rate of the system. Apart from machine learning algorithm, heuristic algorithms also can be used to find the optimal solution in the problem space. Although heuristic approaches doesn't always guarantee the global optimum, the features like achieving an optimal solution within much short time and the ability provide acceptable solution with the right parameters makes it an attractive approach for many application. Heuristic approaches find an optimal solution without hovering over the whole problem space. Therefore, it outperforms typical exhaustive approaches in terms of fewer steps or low latency. However, the computational intensity exponentially increases with the dimension of the problem space for heuristic approaches. One example for the heuristic approach is particle swarm optimization (PSO). It is a heuristic approach of finding optimal solution. This optimization approach is initially introduced by J. Kennedy and R. Eberhart in 1995 [45]. The inspiration of this algorithm is the magical behaviour of a bird flock.. PSO based 3D placement of ABS is studied in [29]. Although it provides an impressive average performance, we couldn't guarantee the performance for a given instance as it is following a heuristic approach. Therefore, completely relying on PSO may results in huge degradation in the system. Moreover, for an N number of UAV, the problem space will have $3N$ dimension which will requires huge computational power as the number of UAV increases.

Considering all these attributes of the algorithms in the state of the art, we propose two algorithms to overcome the identified draw backs. As in [13], the deployment problem can be divided into three phases. Those are 2D deployment, UE assignment and altitude selection. In our both algorithm 2D deployment and UE assignment follows same approaches. 2-D deployment is decided upon clustering algorithm and UE assignment is decided through a matching algorithm. Finally, altitude selection is done through two different approaches. In algorithm I, It does an exhaustive search without allowing

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the altitude diversity. In algorithm II, It enables the altitude diversity and the altitude are decided through an PSO algorithm.

Moreover, there are several other limitations, which do not reflect the realistic attributes of UAV ABSs. In [44], an interference free environment is assumed where CCI is neglected. However, due to the higher probability of LoS propagation in ABS to UE links, CCI from other ABSs is inevitable. Moreover, To reduce the interference, directional antennas are considered in [4]. However, in the other hand directional antennas will throttle the exploitation of spatial diversity which can be achieved for a given height. Our work focuses on fully utilizing the spatial diversity by deploying omnidirectional antennas. Furthermore, effect of LoS is not considered in [41]-[48] for small-scale which can significantly affect the performance in dense urban environments. This article addresses these limitations by proposing a scheme to optimally position a set of ABSs to provide coverage to a group of UEs who has lost connectivity to GBSs due to a disaster. The contributions of this article are four-fold.

- Two algrithms are proposed to position the UAV ABSs and allocate UEs for each ABS, such that the network spectral efficiency is maximized.
- The proposed algorithm is developed for a multi-UAV and multi-UE system, where UEs are randomly distributed in the disaster struck area.
- An adaptive system is developed to cater the effect of LoS propagation for both large-scale pathloss and small-scale fading. Furthremore, CCI from ABSs is also taken into account.
- The scheme is fully distributed with minimal information exchange among the UAVs.

To the best of authors' knowledge, this is the first work which proposes hybrid PSO based optimal UAV deployment and UE association, considering LoS propagation and CCI.

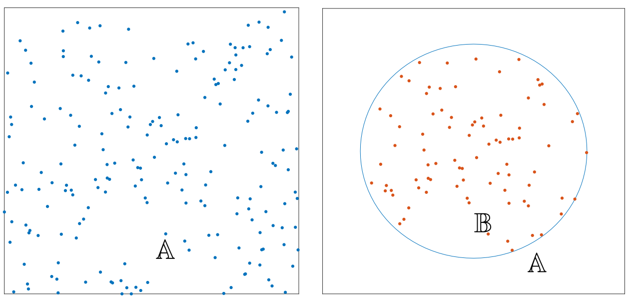
2. System Model

2.1. Spatial Model

Consider an area $\mathbb{A}$, where the UEs are distributed following a homogeneous Poisson point process (PPP) with intensity of λ_U in the 2-dimensional euclidean space $\mathbb{R}^2$. Due to a disaster, the UEs located inside the circular region denoted as $\mathbb{B}$ (centered at the origin of $\mathbb{A}$), have lost the connectivity to the terrestrial network. Fig. 2 illustrates a sample UE distribution. Hereafter, we only focus on the UEs inside $\mathbb{B}$. The average number of UEs in $\mathbb{B}$ is N_{UE}. To serve these UEs, N_{UAV} UAVs are deployed as ABSs. It is assumed that the maximum rate supported by an ABS is R_{UAV}, and the required rate of a UE is r. Therefore, on average, we have,

$$N_{\mathrm{UAV}} = \frac{N_{\mathrm{UE}} \times r}{R_{\mathrm{UAV}}}. \tag{1}$$

Initially, ABSs are deployed randomly in the 3-dimensional space above $\mathbb{B}$. The coordinates of the j^{th} ABS is denoted by $\boldsymbol{A}_j$ and the coordinates of the i^{th} UE is denoted by $\boldsymbol{B}_i$.



(a) (b)

Figure 2. (a). UE distribution in $\mathbb{A}$, (b) UE distribution in $\mathbb{B}$ (coverage-free region)

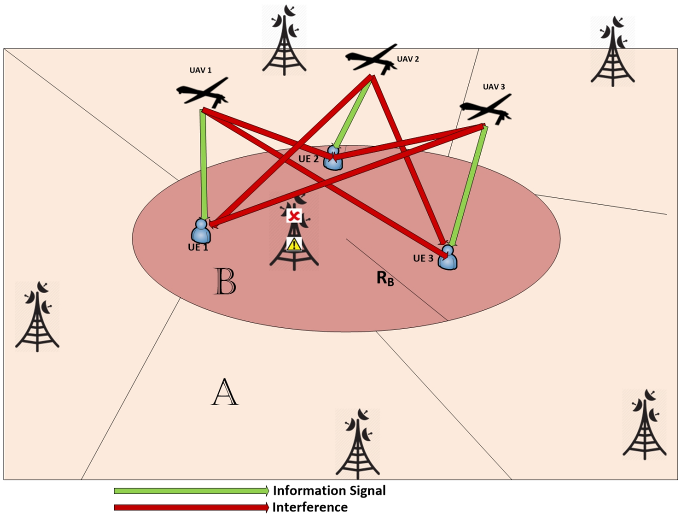


Figure 3. Illustration of information signal and the interference of the system model, $N_{\text{UAV}} = 3$, $N_{\text{UE}} = 3$.

2.2. Channel Model

Since UEs are only served by ABSs, we only focus on the ABS-UE channel. Based on the altitude of the ABSs, the ABS-UE link could experience both LoS and NLoS propagation conditions. To take this into account, the probability of having a LoS ABS-UE link, $P(LOS, \theta_n^m)$, can be calculated based on the elevation angle of an ABS with respect to a UE as[50]

$$P(LOS, \theta_n^m) = \frac{1}{1 + a\exp(-b[\theta_n^m - a])}, \tag{2}$$

where θ_n^m is the elevation angle of the n^{th} ABS with respect to the m^{th} UE, a and b are constants which depend on the environment.

Considering the effects of LoS and NLoS propagation, channel gain from the m^{th} ABS to the n^{th} UE is given as in [3],

$$h_q(m,n) = \frac{|g_q|^2}{\sqrt{(H^2 + d(m,n)^2)^{\alpha_q}}}, \tag{3}$$

where g_q is the small-scale fading amplitude, $q \in \{L, N\}$, L and N refer to LoS and NLoS conditions respectively, H is the altitude of the ABS, $d(m,n)$ is the distance from m^{th} ABS to n^{th} UE and α_q is the large-scale path loss exponent, with $\alpha_L < \alpha_N$ such that the attenuation with LoS propagation is lower that the NLoS case. Here, Rician fading with the Rice factor K is considered for g_L, while g_N follows Rayleigh fading.

2.3. Signal-to-Interference-Plus-Noise Ratio (SINR)

Due to the high probability of having a LoS link with an ABS other than the connected ABS, the interference from other co-channel ABSs on UEs is a crucial factor to be considered when positioning the ABSs[2]. Therefore, in contrast to [2],[5] and [44], we consider the full impact of CCI in the ABS placement and UE association problems. Fig. 3 illustrates a sample scenario of our proposed system. The SINR of the m^{th} UE associated with the n^{th} ABS is given by,

$$SINR(n,m) = \frac{P_r(n,m)}{I_{\text{Agg}}(m) + N_0}, \tag{4}$$

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where $P_r(n,m)$ is the signal power received at m^{th} UE from the n^{th} ABS, $I_{\text{Agg}}(m)$ is the aggregated interference experienced by the m^{th} UE and N_0 is the Gaussian noise power. The received signal power $P_r(n,m)$ can be expressed as

$$P_r(n,m) = p_t^n[P(LOS,\theta_n^m)h_L(n,m) + (1 - P(LOS,\theta_n^m))h_N(n,m)] \ , \tag{5}$$

where p_t^n is the transmitted power of the n^{th} ABS. The aggregate CCI is given by

$$I_{\text{Agg}}(m) = \sum_{l=1,l\neq n}^{N_{\text{UAV}}} p_t^l[P(LOS,\theta_n^m)h_L(n,m) + (1 - P(LOS,\theta_n^m))h_N(n,m)]. \tag{6}$$

3. ABS Placement and User Association Scheme

In this section, we propose two algorithms which infer the position of each ABS and their assigned UE. For simplicity, the problem can be looked into three phases. Those are 2D deployment, UE assignment and altitude selection. Both the algorithms uses similar approaches in terms of 2D deployment and UE assignment. Altitude selection follows different approaches in both the algorithm. 2D deployment is done through a clustering algorithm. The algorithm used in this paper closely follows the principles of K-means clustering. However, in contrast to conventional K-means clustering, our algorithm uses multiple weighting parameters in the decision phase. UE assignment is decided using a matching algorithm. The assignment is modeled as a stable marriage problem with first preference maximized. In algorithm 1, altitude diversity is not considered. ABSs are assumed to be in same altitudes. Then the optimal UE assignment, 2D position and common altitude ($\boldsymbol{H}^{\text{opt}}$) is founded through matching algorithm, clustering and an exhaustive search respectively. Initially, all ABSs are randomly placed above the coverage-free region. The ABSs estimate the locations of the UEs from the uplink signals. Furthermore, it is assumed that each ABS broadcasts the connected UE list and their locations, such that each ABS has essential knowledge on the Network topology. Using this knowledge, each ABS computes the expected signal to interference plus noise ratio (SINR). The expected SINR associated with n^{th} ABS and m^{th} UE is defined as,

$$\mathbb{E}[SINR\,(n,m)] = \mathbb{E}\left[\frac{P_r(n,m)}{I_{\text{Agg}}(n,m) + N_0}\right] \ , \tag{7}$$

This parameter is the one which decides the suitable UE assignment vector (ϕ_m).

Least gain expected (δ) is a constant which decide the minimum $SINR$ increment expected between two subsequent steps.The statistical SINR gain achieved (G_{L}) compared to previous steps is calculated by,

$$G_{\text{L}} = \sum_{all\ i} |\psi(i) - max\{\mathbb{E}[SINR\,(:,i)]\}|, \tag{8}$$

where $\psi(i)$ is the sum of maximum SINR obtained in the previous step. The searching process continuous until the G_{L} is grater than δ. The proposed algorithm is elaborated in Algorithm 1. Notations used in the algorithms are described in Table 1

Fig. 4 illustrates the various stages of clustering for a sample scenario. In our system simulation, $\delta = 0$ because we assume the location of the UEs are still during the whole process. For a highly dynamic UE scenario, we can optimize the δ value to reduce the frequent movement of the ABS, which will be a trade-off between mobility power and system performance.

Algorithm 2 is having altitude diversity. It uses the same approach for 2D positioning and user associations as in Algorithm 1. Apart from that, it enables altitude diversity through particle swarm optimization (PSO) algorithm.

An intelligent approach used by group of birds for searching food or travelling a long distance is captured and simulated in PSO. Essentially, this algorithm keep track on two positions namely

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Table 1. Notation Description

Notation	Description
A_j	Coordinates of the j^{th} ABS
B_i	Coordinates of the i^{th} UE
λ_U	Intensity of the UE distribution
R_b	Radius of the isolated region
N_{UAV}	Required Number of UAVs
N_{UE}	Number of UEs in the isolated region
r	Average required data rate of UEs
R_{UAV}	Maximum rate supported by a UAV
$P(LOS, \theta_n^m)$	probability of line of sight from n^{th} ABS to the m^{th} UE
a , b	Constants which reflects environmental characteristics
$h_q(m,n)$	Channel gain from the m^{th} ABS to the n^{th} UE
H	Height of the ABS
$d(m,n)$	2D euclidean distance from m^{th} ABS to n^{th} UE
α_q	Large-scale path loss exponent
g_q	Small-scale fading amplitude
$P_r(n,m)$	Received signal power at m^{th} UE from the n^{th} ABS
$I_{\text{Agg}}(m)$	Aggregated interference experienced by the m^{th} UE
p_t^n	Transmission power of the n^{th} ABS
ψ	Previous optimal position vector
G_L	Gain achieved comparing to the previous step
δ	Least gain expected
y_i^{opt}	Optimal position (coordinates) of the j^{th} ABS in the present stage
H^{opt}	Optimal height
$S^k(t)$	In PSO space, position of the k^{th} particle at n^{th} iteration
$V_k(n)$	In PSO space, velocity of k^{th} particle at n^{th} iteration
c_1, c_2	Local learning coefficient and swarm learning coefficient respectively
H^{opt}	Optimal height
N_{pop}	Number of particles in the swarm population
N_G	Number of continuous iterations without a gain in the objective function
Γ	Threshold to exit the PSO algorithm

global best and the local best. Global best (X^{Gb}) is the position which is the optimal solution among all the particles in all iteration. Local best (X^{Lb}) is the position which gives the optimal solution of the particular particle in all the iteration. Velocity vector of the particles are calculated based on these two parameter and the inertia of the particle. The velocity of k^{th} particle at n^{th} iteration is given by,

$$V_k(n) = \psi V_k(n-1) + c_1\phi_1(S_k^{\text{Lb}}(n-1) - S_k(n-1)) + +c_2\phi_2(S_k^{\text{Gb}}(n-1) - S_k(n-1)), \tag{9}$$

where $S^k(t))$ is the position of the k^{th} particle at n^{th} iteration. c_1 and c_2 are local learning coefficient and swarm learning coefficient respectively. ϕ_1 and ϕ_2 are positive random numbers. After calculating the velocity, position of the k^{th} particle in the n^{th} iteration will be updated as,

$$S_k(n) = S_k(n-1) + V_k(n). \tag{10}$$

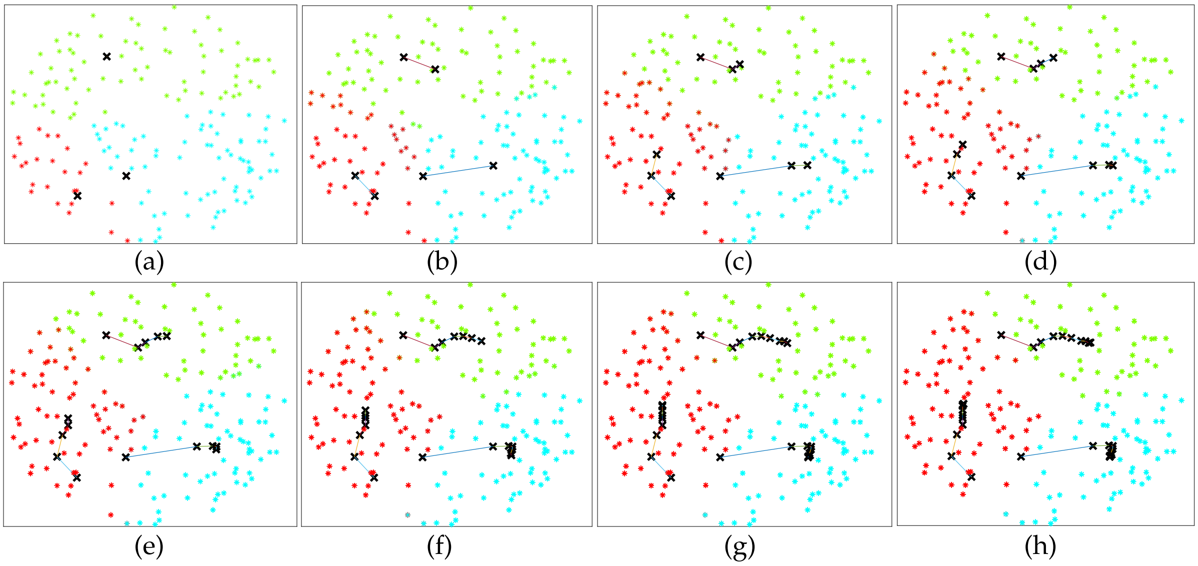

Figure 4. Illustration of the adaptive deployment process, $R_b = 1500m$, $\alpha_N = 2.3$, $\alpha_L = 2$, $\lambda_U = 2 \times 10^{-4}/m^2$, $\delta = 0$ $N_{\text{UAV}} = 3$, $H = 300m$, $r = 15Mbps$, $R_{\text{UAV}} = 1Gbps$. **X**: Shows the position of ABS in the various stages. Three colours differentiate the UE clusters in the particular stage.(a)-(h) shows the 1^{st},2^{nd},3^{rd},4^{th},5^{th},7^{th},$9^{\text{th}}$and 11^{th} stage respectively.

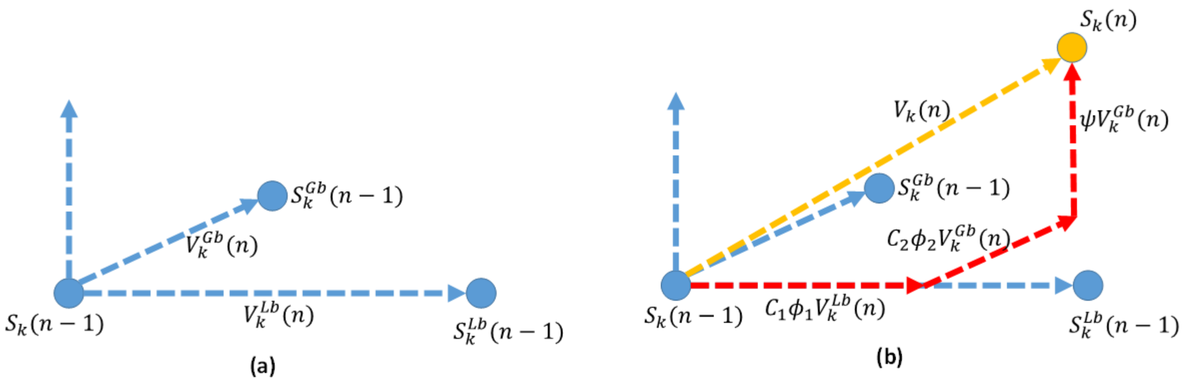

Figure 5. (a) global best, local best, position and the velocity in the $(n-1)^{\text{th}}$ iteration. (b) Velocity in the n^{th} iteration as a weighted vector addition of previous velocity components and the position in the n^{th} iteration

Fig. 5 illustrates the movement of a single particle in the n^{th} iteration.

4. Simulation Results And Discussion

In this section, the performance of both the algorithms are illustrated through numerical simulation. Algorithm 1 is compared with the random and linear deployment of ABS in terms of total spectral efficiency (TSE) and average coverage ($\overline{P_{\text{COV}}}$) probability. With the assumption of perfect backhaul, TSE is given by,

$$TSE = \sum_{m=1}^{N_{\text{UAV}}} \sum_{n=1}^{N_{\text{m}}} \log_2(1 + SINR(n,m)), \tag{11}$$

where N_{m} is the number of associated UEs of m^{th} ABS. $\overline{P_{\text{COV}}}$ is given by,

$$\overline{P_{\text{COV}}} = \frac{N_{\gamma_{\text{th}}}}{N_{\text{UE}}}, \tag{12}$$

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Algorithm 1: Clustering and matching algorithm with exhaustive search

Data: $\boldsymbol{B_i}$, $\boldsymbol{A_j}$ for all i, j α_L, α_N, $\mathbb{E}[g_L]$,$\mathbb{E}[g_N]$,H_l for all l ∈{1,....,N_H

Result: H^{opt}, ($\boldsymbol{y}_j^{\text{opt}}$) and (ϕ_i) , for each i ∈{1,....,N_{UE}} and j ∈{1,....,N_{UAV}}

begin
- **for** $l = 1, \ldots.., N_H$ **do**
  - H_l is the height of the ABS.
  - **Block-A**
    - **while** $G_L > \delta$ **do**
      - **for** $i = 1, \ldots.., N_{UE}$ **do**
        - Obtain the optimal UE assignment
        - **for** $j = 1, \ldots.., N_{UAV}$ **do**
          - Calculate the $\mathbb{E}[SINR]$ for different cases
          - **switch** j **do**
            - **case** *1* **do**
              - $\mathbb{E}[SINR\,(1, i)] = \mathbb{E}\left[\frac{P_r(1,i)}{I_{\text{Agg}}(1,i)+N_0}\right]$
            - ...
            - ...
            - **case** N_{UAV} **do**
              - $\mathbb{E}[SINR\,(\text{N}_{\text{UAV}}, i)] = \mathbb{E}\left[\frac{P_r(\text{N}_{\text{UAV}},i)}{I_{\text{Agg}}(\text{N}_{\text{UAV}},i)+N_0}\right]$
        - $\phi_i = \tau$, where $\mathbb{E}[SINR\,(\tau, i)] = max\{\mathbb{E}[SINR\,(\,:\,, i)]\}$
      - $G_{\text{L}} = \sum_{n=i}^{N_{\text{UE}}} |\psi(i) - max\{\mathbb{E}[SINR\,(\,:\,, i)]\}|$
      - $\psi(i) = \mathbb{E}[SINR\,(\tau, i)] : i \in \{1, 2..., \text{N}_{\text{UE}}\}$
      - **for** $j = 1, \ldots.., N_{UAV}$ **do**
        - Obtain the optimal 2D position
        - **switch** ϕ_i **do**
          - **case** *1* **do**
            - $\boldsymbol{y}_1^{\text{opt}} = weighted\ mean\{\boldsymbol{x}^{\mathbf{1}}\}$
          - ...
          - ...
          - **case** N_{UAV} **do**
            - $\boldsymbol{y}_{\text{N}_{\text{UAV}}}^{\text{opt}} = weighted\ mean\{\boldsymbol{x}^{\text{N}_{\text{UAV}}}\}$
  - $\mathbb{E}[TSE\,(l)] = \sum_{i=1}^{N_{\text{UE}}} \log_2(1 + max\{\mathbb{E}[SINR\,(\,:\,, i)]\})$
- $H^{\text{opt}} = H_k$, where $\mathbb{E}[TSE\,(k)] = max\{\mathbb{E}[TSE]\}$

$\boldsymbol{x}^k$ refers to the coordinates of the UEs assigned to k^{th} ABS.

where $N_{\gamma_{\text{th}}}$ is the number of users experiencing $SINR$ greater than the threshold $SINR$ (γ_{th}) value which can be used to reflect the QoS requirement.

For the simulation purpose, we consider $\mathbb{A}$ as $6 \times 6\ km^2$ and $\mathbb{B}$ with $R_c = 2000\ m$. UE intensity $\lambda_U = 2 \times 10^{-4}/m^2$, $\delta = 0$, $\text{N}_{\text{UAV}} = 3$, Rice factor k=1.5, pathloss parameter $\alpha_L = 2, \alpha_N = 2.5$, noise variance $N_o = -70\ dBm$, transmitted power of the ABS $p_t = 30\ dBm$ (all the ABSs are having equal transmit power).

Algorithm 1 is compared for all four general environmental conditions (suburban, urban, dense urban, highrise urban). Fig. 7 shows the simulation results for the total spectral efficiency against the height of the ABS for both ML based deployment and random deployment. Moreover, we compared it with uniform and random deployment for suburban and highrise urban environments which is illustrated in Fig.8.

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Algorithm 2: Clustering and matching algorithm with PSO

Data: B_i , A_j for all i, j
$\alpha_L, \alpha_N, \mathbb{E}[g_L],\mathbb{E}[g_N],H_l$ for all $l \in\{1,....,N_H$
Result: H^{opt}, (y_j^{opt}) and (ϕ_i) , for each $i \in\{1,....,N_{\text{UE}}\}$ and $j \in\{1,....,N_{\text{UAV}}\}$
begin
  Initialize random height for all ABS

  Execute **Block-A** and **Block-B** to find the optimal UE assignment and 2D position for the given height. (This UE assignment vector and 2D- placement will be the initial parameters for all the particle in the population)
  $n_i = 1$
  for $k = 1, ..., N_{pop}$ **do**
    Initialize random positions (heights) $X_k(n_i)$ for k^{th} particle
    Initiate particle velocity ($V_k(n_i)$) as unit value.
    Update UE assignment and 2D position by executing **Block-A**
    Calculate the objective function $J_k(n_i) = \mathbb{E}[TSE]$
    Update $X_k^{\text{Lb}}(n_i)$ and $X_k^{\text{Gb}}(n_i)$
  while $N_G > \Gamma$ **do**
    for $k = 1, ..., N_{pop}$ **do**
      Calculate $V_k(n_i + 1)$ as per 9
      Update the new position $X_k(n_i + 1)$ as per 10
      Update UE assignment and 2D position by executing **Block-A**
      Calculate the objective function $J_k(n_i + 1) = \mathbb{E}[TSE]$
      Update $X_k^{\text{Lb}}(n_i + 1)$ and $X_k^{\text{Gb}}(n_i + 1)$
    if ($X_k^{Gb}(n_i + 1)$= $X_k^{Gb}(n_i)$) **then**
      $N_G = N_G + 1$
    else
      $N_G = 0$
    $n_i + +$
  H^{opt} = $X_k^{\text{Gb}}(n_i + 1)$;

Fig. 7 and Fig. 8 clearly illustrates that the Algorithm 1 outperforms the random and uniform deployment. The behavior can be explained with the help of Fig. 6, which illustrates how the PLoS will be effected by the elevation angle for different types of environments. It is obvious that the pathloss will increases with the height of the ABS which should reduce the total spectral efficiency. However, on the other hand the elevation angle also increases with the height resulting higher PLoS which dominates pathloss effect and increase the spectral efficiency. Once it reaches the height where gradient start decreasing (Fig. 2 [50]) the PLoS will be almost constant (insignificant increment) where pathloss effect starts to dominate the $SINR$. As a result, it decreases the spectral efficiency. That critical point where pathloss begins to dominate PLoS will give the optimal altitude. furthermore, it is observable that TSE in each and every scenario merge together for higher ABS altitudes regardless of the environmental condition. This is because for huge altitude ($\theta \approx 90^o$) almost $PLoS = 1$ regardless of the environmental condition. Therefore, TSE solely depends on pathloss which is almost same for each and every UE (Distance between the UE's are negligible in extremely higher altitudes). This observation witness that in lower altitude platforms (LAP), interference have a huge effect in the performance of the system. Therefore it should be intelligently managed to gain better system performance. which leads to a conclusion our proposed model intelligently positions the ABS where it gives a better system performance.

To compare the system performance in terms of coverage probability we adopt to the optimal altitude proposed by our algorithm. Height of the ABS is considered as 420 m, 980 m, 1260 m and 1890 m for suburban, urban, dense urban and high rise urban respectively. Other parameters are same

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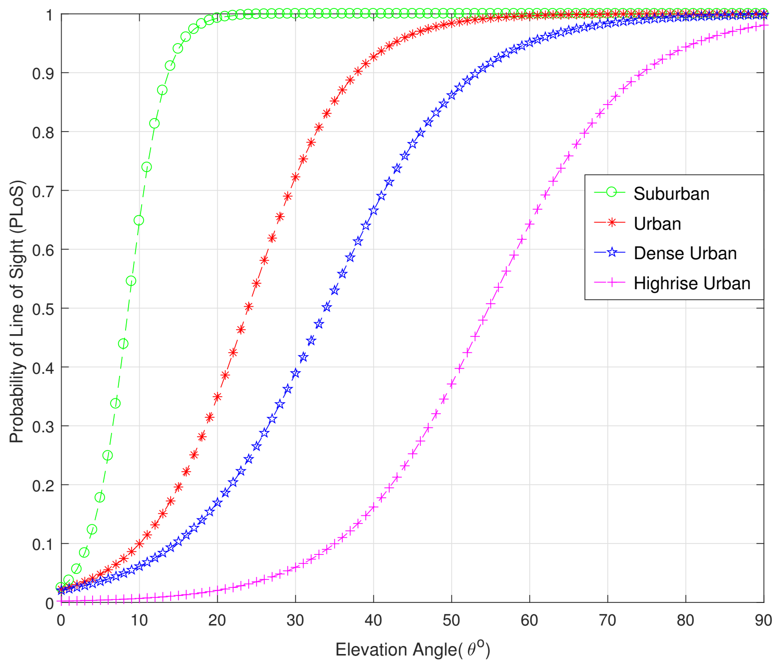

Figure 6. Probability of line of sight(PLoS) vs Elevation angle

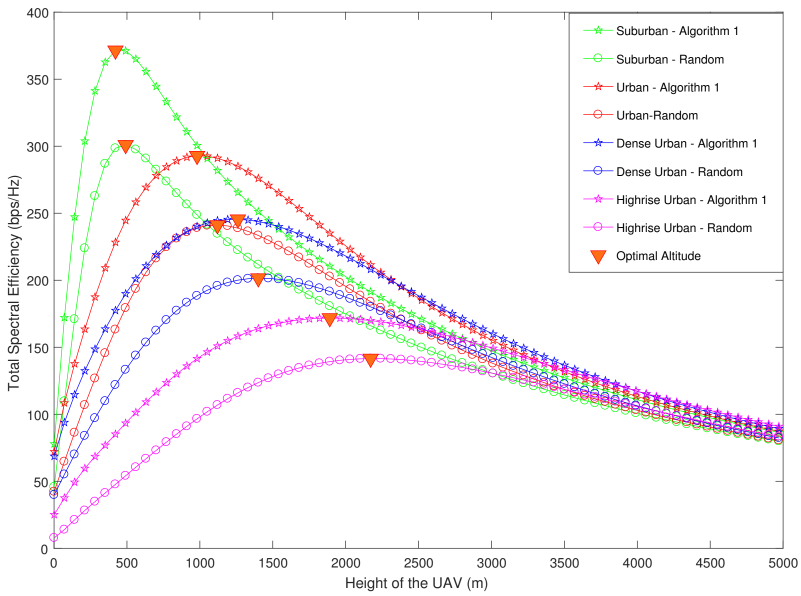

Figure 7. Total spectral efficiency vs Height of the ABS (Comparison between ML based deployment and random deployment)

as the previous simulation. Fig. 9 shows how the coverage probability behave with SINR threshold. it is conspicuous that the average coverage probability of Algorithm 1 performs better comparing to random deployment.

Performance of Algorithm 2 is compared with respect to the performance of Algorithm 1. performance gain of Algorithm 2 (P_{Gain}) is calculated as the difference between the optimal total spectral efficiency (TSE) obtained by both the algorithms,

$$P_{\text{Gain}} = TSE_2^* - TSE_1^* \ , \tag{13}$$

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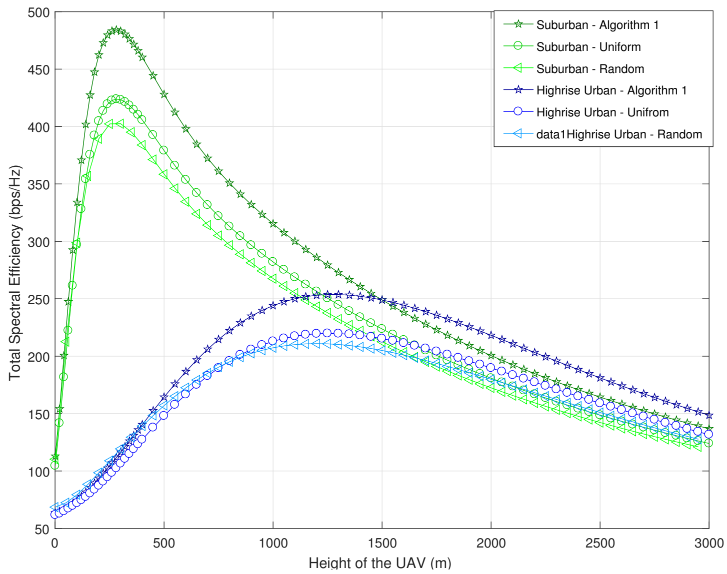

Figure 8. Total spectral efficiency vs Height of the ABS (Comparing ML based deployment random deployment and linear deployment)

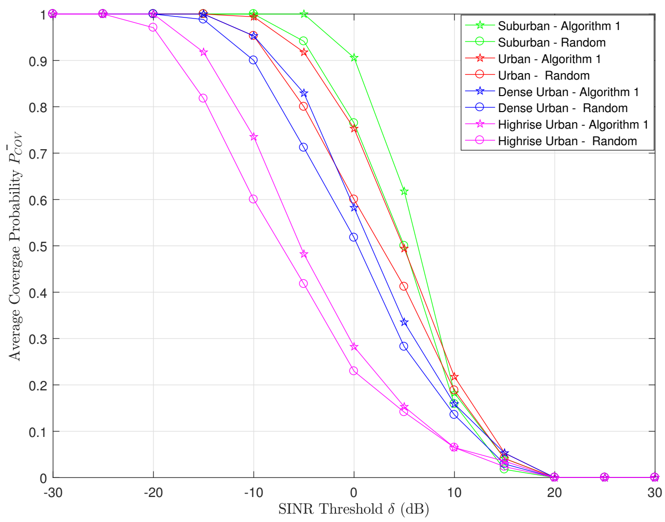

Figure 9. Average Coverage Probability vs SINR Threshold (Comparison between ML based deployment and random deployment)

where TSE_2^* and TSE_1^* are optimal TSE obtained through Algorithm 2 and Algorithm 1 respectively.

Fig. 10 shows the performance gain of Algorithm 2 vs the amplitude of LoS component (S) for suburan and highrise urban environment. Fig. 7 and Fig. 8 witness that Algorithm 1 perform better than random and linear deployment. At the same time, Fig. 10 witness that Algorithm 2 performs better than Algorithm 1. which concludes that Algorithm 2 will perform much better than random and uniform deployment. However, the trade off comes with complexity. Algorithm 2 is bit more complex as it enables altitude diversity. Also it is observable that performance of algorithm 2 is increasing with the LoS component's power.

Algorithm 2 is having altitude diversity. To improve the performance through it, the algorithm will diversify altitude which gives higher probability of LoS (PLoS) with minimal effect in the pathloss. If LoS power is very low it is not possible to take advantage by increasing PLoS. Therefore, Algorithm

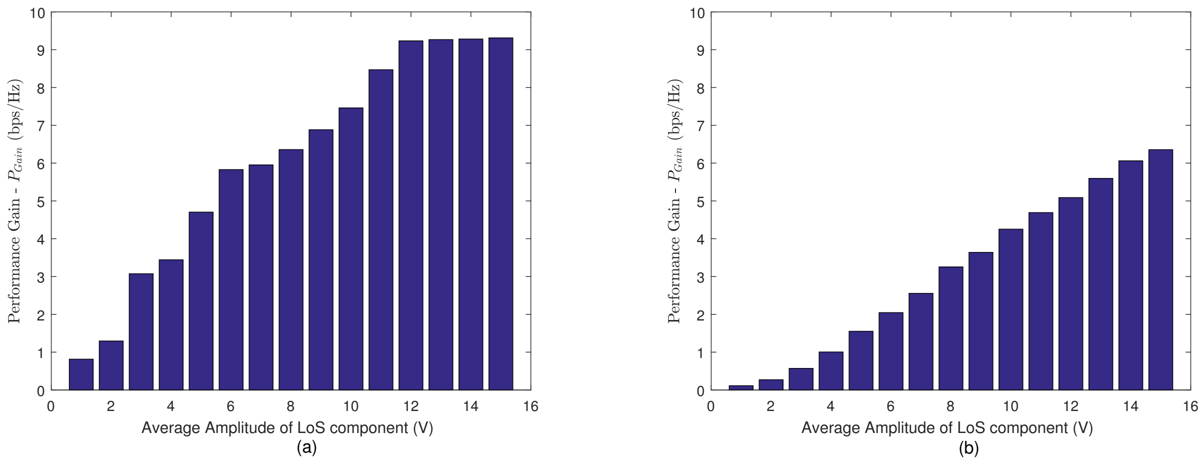

Figure 10. Performance Gain vs Average strength of LoS component (a) Suburban (b) Highrise Urban

2 performs much better in higher LoS power scenarios. Also it is notable that suburban case having higher performance gain compared to highrise urabn environment. This is due to the PLoS behaviour of different environments. It is observable in Fig. 6, for suburban environment, we can make a dratic change in PLoS by making a small adjustment in the elevation angle compared to high rise urban case where it would demand a huge change in elevation angle. As it mentioned earlier, Algorithm 2 take advantage of altitude diversity by increasing the PLoS, in suburban environment, it is possible to get higher PLoS with minimal altitude change. Effectively, without much increase in the pathloss which makes Algorithm 2 more effective in suburban case. Although Algorithm 2 gives better performance, it is computationally intense as it enables altitude diversity. If there are any computational constraints we can prefer Algorithm 1 yet it will perform better than typical deployment strategies. Therefore we can choose between both the algorithm based on the deployment scenario, environment and resource constraints.

5. Conclusions

This article proposed two algorithms for optimal deployment and UE assignment of UAV ABSs in a disaster region for randomly distributed UEs. The proposed algorithms intelligently manage the interference to search for the sub-optimal position and the UE assignment. The only difference between both algorithms is altitude diversity. The first algorithm does not allow altitude diversity which makes that less complex as compared to the other. The second algorithm allows the altitude diversity which gives higher performance over the other. Depending on the deployment scenario, requirements and the environment, the advantages and disadvantages of both algorithms have been identified. The first approach is vigorous for a system with a limited computational resource or lower probability of LoS while the second approach is appropriate for data rate greedy systems or a higher probability of LoS links. Performance of both algorithms are verified for a worst case scenario in terms of interference, where all the UEs are experiencing the CCI. Simulated results ensured the robustness of the proposed algorithms against the random deployment by resulting higher total spectral efficiency, lower optimal altitude and higher average coverage probability.

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