

3D placements of drones in a millimeter-wave network to maximize the lifetime of wireless devices

Wa'ed Malkawi*, Hazim Shakhathreh, Ahmed Musa

Department of Telecommunications Engineering, Hijawi Faculty for Engineering Technology, Yarmouk University, Irbid, Jordan

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ABSTRACT

In the last few years, the use of drones is increasing day by day in wireless networks and the applications of them are rapidly increased on different sides. Now, we can use the drone as an aerial base station (BS) to support cellular networks in emergency cases and in natural disasters. To take the advantage of both drones and fifth-generation (5G) and link between their features, we study an aerial BS considering millimeter waves (mm-waves). In this paper, we optimize the 3D placements for multiple unmanned aerial vehicles (UAVs) in an mm-wave network to achieve maximum time durations of the uplink transmission. First, we present a formulation for the placement problem, where we aim to allocate 3D locations for multiple UAVs to achieve the maximum sum of time durations of uplink transmissions. We propose an efficient algorithm to find the placements of UAVs. We propose an algorithm that starts by grouping the wireless devices into a number of clusters, and each cluster is served by a single UAV. After the clustering process, it applies the gradient projection-based algorithm (GP) or particle swarm optimization (PSO) in each cluster. In the results section, our proposed approach and the center projection algorithm will be compared to prove the efficiency of our approach.

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1. Introduction

Recently, we notice an increase in research on drones in wireless communication especially in cellular networks, as they are used as aerial base stations to support damaged or crowded terrestrial base stations. As described in Zeng et al. (2016b), drones are also used for several purposes in wireless communication such as providing connectivity to the core network, providing wireless connection between distant devices that have no line of sight (LOS) connection between them, and collecting data from a distributed wireless devices. Sawalmeh et al. (2017), and Shakhathreh et al. (2017a; 2017b; 2017c) used a UAV in providing wireless coverage in emergency cases or special events for users are proposed.

It is worth noting that, previous studies on the use of drones as a source of wireless coverage take into account the downlink scenario. In Khawaja et al.

(2017); the authors studied the characterization of mm-wave air to ground channels for UAV communication. Compared with the few works that have been done from an uplink perspective. Azari et al. (2018) analyzed the uplink performance of a drone cell in a random field of ground interference. Zeng et al. (2016a) studied how to maximize the throughput in UAV relaying systems using the optimization of source/relay transmit power along with the UAV trajectory, taking into account the practical mobility constraints. Yang et al. (2018) explained a system for data collection using a UAV that sends a UAV to collect data from ground terminals. Their goal is to find optimum transmit power of ground station and the trajectory of UAV which achieve different Pareto optimal energy tradeoffs between the ground station and the UAV.

One of the enabling technologies for the 5G is the mm-wave, which is characterized by its short wavelength and high frequencies in addition to the availability of large bandwidth (Niu et al., 2015), which serves the requirements of the 5G to increase the data rate and provide services to a greater number of users. Communication in mm-waves networks needs LOS link as possible to guarantee reliability (Sekander et al., 2018). On the other hand, a drone has the ability to move and hover, hence it

* Corresponding Author.

Email Address: 2018976003@ses.yu.edu.jo (W. Malkawi)

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Corresponding author's ORCID profile:

<https://orcid.org/0000-0002-1227-0302>

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can guarantee LOS links, and hence we can guarantee the more reliable communication.

Note that, [Shakhatreh and Khreishah \(2018\)](#) found the optimal placement of a UAV, and the aim is to allocate the location for one UAV that achieves the maximum sum of uplink transmissions time durations. [Shakhatreh et al. \(2019\)](#) expanded the field of research to include multiple UAVs. Now, in [Shakhatreh and Khreishah, \(2018\)](#), and [Shakhatreh et al. \(2019\)](#), mm-waves have not been considered, while [Shakhatreh and Malkawi \(2020\)](#) found the optimal placement of a UAV, and the aim is to allocate the location for one UAV that achieves maximum sum of uplink transmissions time durations on the basis that the frequencies used are mm-waves. In this paper, we will expand the field of research to include multiple UAVs considering the same conditions in [Shakhatreh and Malkawi \(2020\)](#).

Drones are one of the supplements of 5G. We can use drones in 5G as mobile hot spots during disaster situations; when the ground BSs or even the electrical infrastructure are damaged and when the users are out of service or they can't recharge their wireless devices. As evidence of this situation is Hurricane Katrina, where about 700,000 customers in Louisiana lost power also almost 200,000 in Mississippi ([Akdeniz et al., 2014](#)). Because of the hovering characteristic of the drones, they can guarantee LOS connectivity with the desired user. Thus, we have fulfilled the requirements for using mm-waves which is to reduce the blockage probability and so maintain data rate requirements for high throughput mobile applications in 5G. To our best knowledge, 3D placements of UAVs in the mm-wave network to maximize the wireless devices' lifetime have not been studied yet. Therefore, this motivates us to investigate this problem. The contributions of this paper are summarized as follows:

- We formulate a problem to find optimal placements of multiple UAVs and the aim is to obtain maximum lifetime for the wireless devices.
- We use a k-means algorithm for clustering the ground users into k clusters, then we use the GP algorithm for each cluster to obtain an optimal placement for each UAV to obtain maximum lifetime for the uplink transmission.
- We propose a PSO in case the coverage angle doesn't meet the condition of concavity.

2. System model

Let (X_u, Y_u, Z_u) symbolize the 3D location of a drone u where $u \in U$. Also, assume $|I|$ a number of ground users and each user has a 2D location (we can approximate the location for each user using received signal strength indicator (RSSI) as shown in [Shakhatreh et al. \(2019\)](#) and they distributed according to $f(x, y)$, in I , mentioning that user $i \in I$ with E_i as remaining energy in his/her wireless device (the ground user can announce the drone

his/her E_i by sending control messages) and P_{\max} as maximum transmit power. We assume that the ground users in an uplink scenario transmit their information to the UAVs in U using a technique of frequency division multiple access (FDMA) to achieve a data rate R and keeping the channels with no interference between each other as done in [Shakhatreh et al. \(2019\)](#), where the backhaul links interconnected the UAVs together and then to the core of the internet in order to support them. Also, let only one UAV will serve each user $i \in I$ for τ_{iu} seconds and τ_{iu} must be greater than threshold τ_{th} and it depends on the residual energy E_i for the ground user. Also, it depends on the location of UAV $u \in U$.

For mm-wave, we propose suitable path loss models for LOS and non-line of sight (NLOS) links as found in [Akdeniz et al. \(2014\)](#) which given as in Eq. 1:

$$\begin{aligned} L_{L,iu} &= \alpha_L + 10\beta_L \log_{10}(d_{iu}) & \text{LOS links} \\ L_{N,iu} &= \alpha_N + 10\beta_N \log_{10}(d_{iu}) & \text{NLOS links} \end{aligned} \quad (1)$$

where $\alpha_L, \beta_L, \alpha_N$, and β_N are the parameters of the LOS and NLOS path loss models, and distance $d_{iu} = \sqrt{(X_u - x_i)^2 + (Y_u - y_i)^2 + (Z_u)^2}$ is measured between a wireless device for the user i and a UAV u .

Besides, we will not ignore the effect of human body blockage, and we propose the probability of LOS, P_L , for a user i as shown in [Gapeyenko et al. \(2018\)](#) that given in Eq. 2:

$$P_L(\theta_i) = \exp\left(-\lambda g b \frac{z_b - z_i}{\tan(\theta_i)}\right) \quad (2)$$

Assuming θ_i is the coverage angle measured between the UAV and a ground user as shown in [Fig. 1](#), λ denotes human blocker's density, $g b$ denotes the human blocker's diameter, z_b denotes the human blocker's height, and z_i denotes the receiver's height.

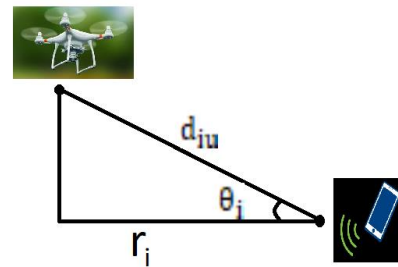


Fig. 1: Coverage angle θ_i

Then, we can calculate the average path loss from Eq. 3:

$$L_{a,iu} = P_L(\theta_i)L_{L,iu} + [1 - P_L(\theta_i)]L_{N,iu} \quad (3)$$

3. Problem formulation

We assume that there is a transmission between a user allocated at (x_i, y_i) and a drone allocate at (X_u, Y_u, Z_u) . Then each user's data rate is C_{iu} that found from Eq. 4:

$$C_{iu} = B_i \log_2 \left(1 + \frac{p_{iu}/L_{a,iu}}{N} \right) \quad (4)$$

Mentioning that B_i symbolizes the transmission bandwidth for the user i , p_{iu} denotes the power transmission from user i to the UAV u , $L_{a,iu}$ denotes the average loss for the path from user i to UAV u , and N denotes the power of the noise.

We assume that for each user there is a similarity in data rate R , and the channel bandwidth for each user equal $B/|I|$, where B indicates the overall system bandwidth. And here we must mention a concept of the FDMA, that gives each user one sub-channel for communications which prevents interference during transmissions between users. From Eq. 5 we can find the minimum power p_{iu} wanted to achieve a similar data rate R for all users:

$$p_{iu} = \left(2^{\frac{R \cdot |I|}{B}} - 1 \right) \cdot N \cdot L_{a,iu} \quad (5)$$

In this paper, we aim to find the optimal locations of multiple UAVs in U where we can maximize T which denotes the sum of all uplink transmissions' time durations. We can formulate our problem as:

$$(X_u, Y_u, Z_u, \tau_{iu}, w_{iu}) \max T = \sum_{u=1}^{|U|} \sum_{i=1}^{|I|} w_{iu} \tau_{iu}$$

Subject to:

$$\sum_{u=1}^{|U|} w_{iu} = 1, \forall i \in I \quad (6.a)$$

$$w_{iu} \left(2^{\frac{R \cdot |I|}{B}} - 1 \right) \cdot N L_{a,iu} \leq P_{max}, \forall i \in I, \forall u \in U \quad (6.b)$$

$$w_{iu} (\tau_{iu} - \tau_{th}) \geq 0, \forall i \in I, \forall u \in U \quad (6.c)$$

$$w_{iu} \tau_{iu} \left(2^{\frac{R \cdot |I|}{B}} - 1 \right) \cdot N L_{a,iu} \leq E_i, \forall i \in I, \forall u \in U \quad (6.d)$$

$$x_{min} \leq X_u \leq x_{max}, \forall u \in U \quad (6.e)$$

$$y_{min} \leq Y_u \leq y_{max}, \forall u \in U \quad (6.f)$$

$$z_{min} \leq Z_u \leq z_{max}, \forall u \in U \quad (6.g)$$

In the problem formulation, multiple UAVs belonging to U serve the group of the users I . Also, we define a binary variable w_{iu} which we give it value 1 in case that UAV u serves user i and otherwise the value will be 0. In this objective function, we can maximize the uplink transmission time by determining the optimal placements for the UAVs in U . For achieving maximum T , we will allocate each user to its closest UAV. The constraint in (6.a) ensures a connection to no more than one UAV for each user. The constraint (6.b) guarantees that each wireless device transmits the power of no more than its maximum transmit power P_{max} . The constraint (6.c) ensures that the serving time for each user $i \in I$ by UAV is greater than the threshold time τ_{th} seconds. The constraint (6.d) guarantees that the user's device consumes energy no more than its residual energy E_i . The constraints (6.e-6.g) show the minimum and maximum limitations on X_u , Y_u , and Z_u , respectively, that could achieve the safety of the drone (Yang et al., 2018).

4. Proposed algorithm

Because of the intractability of problem 6, we suggest clustering the ground users. We took inspiration from the k-means clustering algorithm (Hartigan and Wong, 1979). Where the goal is to cluster $|I|$ points into k groups where every single point belongs to the group with the closest mean. Firstly, we have the $|I|$ locations (x_i, y_i) , $\forall i \in I$, and we set the number of UAVs $k=|U|=2$. Then we start placing k -centroids in a random location. After that, we repeat the following steps until it converges (when there is no change in the assignments): 1) for each point we choose the nearest centroid and the point is assigned to it. 2) for each cluster we calculate the mean of all points assigned to and move the centroid there. Here it is worth noting that the computational complexity for the k-means algorithm is $O(nkt)$ (Na et al., 2010).

Now, we can describe the whole process to solve our main problem 6 in a flowchart shown in Fig. 2.

We assume only one UAV to cover each cluster. First, we set the number of drones to be $|U|=2$ and then clustering the users using k-means algorithm. After that, in each cluster, we consider that z_{min} ensures a 100% LOS connection between the user's device i and the UAV. By this, we have relaxed our goal to find the optimum 2D location of the UAV in order to maximize the lifetime of wireless devices. After all of these, we found that we can represent the constraint sets (6.b-6.d) by an intersection of half spheres and this intersection forms a convex set in terms of (X_u, Y_u) , so, we can write our problem in a form of a two-variable (X_u, Y_u) optimization problem (as proved in Shakhathreh and Malkawi (2020)) and we note the resulted objective function is concave if the coverage angle θ_i for all ground users in a cluster is greater than 60° (as proved in Shakhathreh and Malkawi (2020)). Now, in case the objective function is concave, we can find the optimal location of a UAV using the gradient projection algorithm (Bertsekas and Tsitsiklis, 1989) which has a computational complexity $O(M)$ (Jiang et al., 2014). The GP algorithm is given by:

$$(X_u, Y_u)^{n+1} = [(X_u, Y_u)^n + \gamma \cdot \nabla F((X_u, Y_u)^n)]^+ \quad (7)$$

Here, n is the number of iteration, γ is a step size with a positive value, ∇F is the gradient of the objective function and we denote the orthogonal projection of vector q onto convex set Q with $[q]^+$. Mentioning that $[q]^+$ is defined by:

$$[q]^+ = \arg \min_{w \in Q} \|w - q\|_2 \quad (8)$$

The pseudo-code of the GP algorithm is shown in Fig. 3a (Shakhathreh and Malkawi, 2020) as algorithm 1. Fig. 3b shows the PSO algorithm's pseudo-code as algorithm 2.

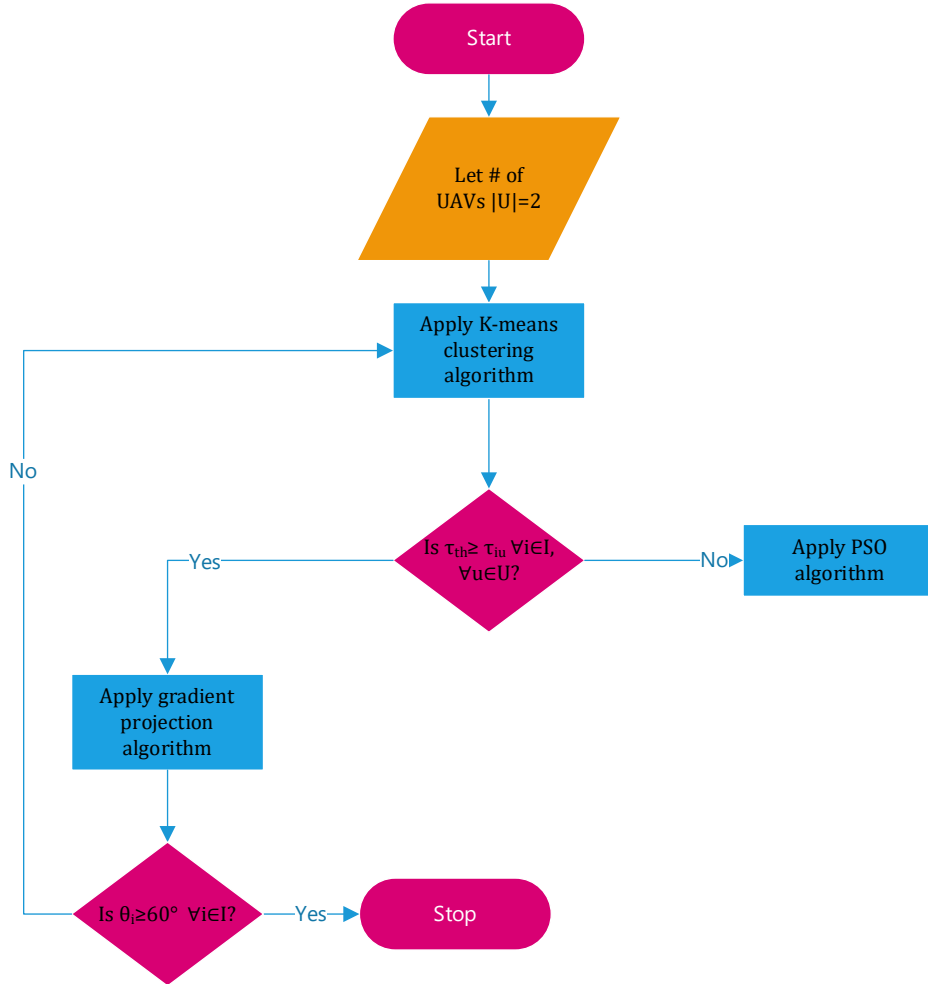


Fig. 2: Flowchart for solving the main problem

(a) Algorithm 1 GP algorithm	
Input: The step tolerance ϵ , The step size γ The maximum number of iterations n_{max}	
Initialize (X_u, Y_u)	
For $n=1,2,\dots,n_{max}$	
$(X_u, Y_u)^{n+1} = [(X_u, Y_u)^n + \gamma \cdot \nabla F((X_u, Y_u)^n)]^+$	
If $\ (X_u, Y_u)^n - (X_u, Y_u)^{n+1} \ < \epsilon$	
Return: $(X_u, Y_u)_{opt} = (X_u, Y_u)^{n+1}$	
End for	
(b) Algorithm 2 Particle swarm optimization algorithm	
1. Initialization. For each of the N particles:	
a. Initialize the position $x_i(0) \forall i \in 1:N$	
b. Initialize the particle's best position to its initial position $p_i(0) = x_i(0)$	
c. Calculate the fitness of each particle and if $f(x_i(0)) \geq f(x_j(0)) \forall i \neq j$ initialize the global best as $g = x_i(0)$	
2. Until a stopping criterion is met, repeat the following steps	
a. Update the particle velocity according:	
$v_i(t+1) = v_i(t) + c_1(p_i - x_i(t))R_1 + c_2(g - x_i(t))R_2$	
b. Update the particle position according:	
$x_i(t+1) = x_i(t) + v_i(t+1)$	
c. Evaluate the fitness of the particle $f(x_i(t+1))$.	
d. If $f(x_i(t+1)) \geq f(p_i)$, update personal best: $p_i = x_i(t+1)$	
e. If $f(x_i(t+1)) \geq f(g)$, update personal best: $g = x_i(t+1)$	
At the end of the iterative process, the best solution is represented by g .	

Fig. 3: (a) GP algorithm, (b) PSO Algorithm (Marini and Walczak, 2015)

When the optimization problem is not concave, then a heuristic algorithm must be used to find the optimal location of a UAV, which is a PSO algorithm with a computational complexity of $O(N \log N)$

(Gheitanachi et al., 2010). The PSO algorithm is given by:

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (9)$$

Here, t is the iteration number, x_i represent the position of the i^{th} particle in 2D space and is represented as: $x_i = [x_{i1} \ x_{i2}]$, v_i is the velocity of the i^{th} particle and is represented as $v_i = [v_{i1} \ v_{i2}]$ and is given by:

$$v_i(t+1) = v_i(t) + c_1(p_i - x_i(t))R_1 + c_2(g - x_i(t))R_2 \quad (10)$$

where, c_1 c_2 are acceleration constants, R_1 R_2 are diagonal matrices of random numbers generated from a uniform distribution in $[0,1]$, p_i is the personal best, and g is the so-called global best.

Finally, as shown in the flowchart in Fig. 2, we check the constraint (6.c) if satisfied or not, if not, the number of drones $|U|$ will be increased by one and the convergence will be followed by re-executing the previous steps.

5. Simulation results

We use Matlab to show the efficiency of using the proposed algorithm shown in Fig. 2. We compare the performance of using either gradient projection or PSO algorithms and using the center projection

algorithm which assigns the best locations in the center of the coverage region.

We simulate an area of $1000 \times 1000 \text{m}^2$ which has 500 users distributed refer to two scenarios (uniform, non-uniform), each wireless device has residual energy of E_i , and the threshold value of uplink transmission's time duration equal τ_{th} . We apply the k-means clustering algorithm to find the optimal clustering in each scenario, then we assume different values for z_{min} , and according to these values we use either GP algorithm or PSO algorithm, and then compare their solutions with center projection algorithm solution. Table 1 lists the simulation parameters.

5.1. Uniform distributed users

We assume that users distributed in a uniform manner in the region of $1000 \times 1000 \text{m}^2$, we have started applying the proposed algorithm (shown in Fig. 2) to detect the suitable number of drones to serve the region in order to achieve maximum T considering the given constraints in 6.

When we applied the k-means clustering algorithm, we found that the best number of clusters for the given simulation parameters, equal 4 clusters assuming we will put the UAVs at 700m altitude and only 2 clusters assuming we will put the UAVs at an altitude equal to 300m. To see the clusters resulted in the two cases, see Figs. 4a, and 4b.

Table 1: Parameters used in simulation results

Parameter	value
Dimensions of area	$1000 \times 1000 \text{m}^2$
Number of ground users	500 users
Maximum number of iterations n_{max}	100
Energy of each wireless device E_i	$9000 + 9000 * \text{rand}(500,1)$
Data rate R	100Mbps
Total bandwidth	5GHz
Noise power	10^{-14}W
Threshold time duration of uplink transmission τ_{th}	900 seconds
α_L, β_L	(61.4, 2)
Carrier frequency	28GHz

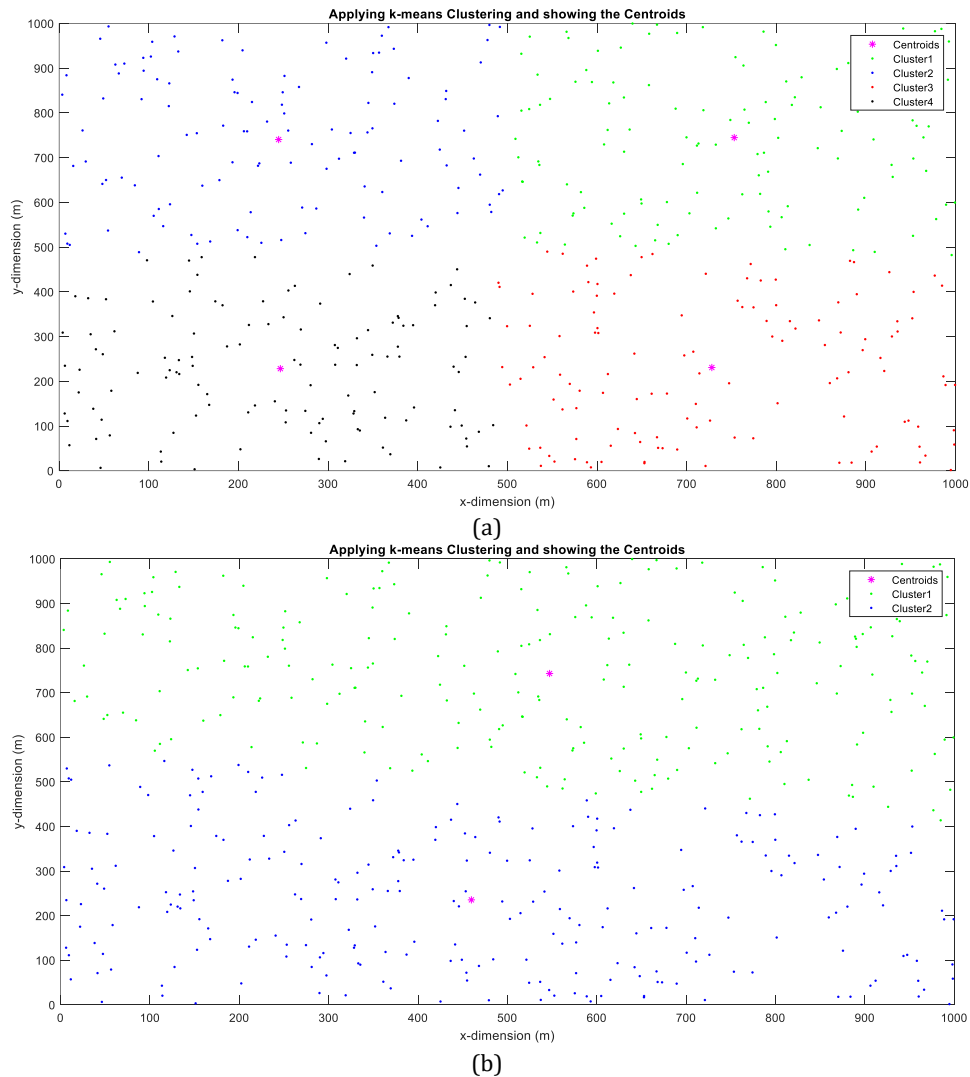


Fig. 4: K-means clustering applied to cluster the uniform users at (a) $z_{min} = 700\text{m}$, (b) $z_{min} = 300\text{m}$

After clustering the users, it is time to apply either GP or PSO algorithms. For UAVs with an altitude of 700m that fulfills the concavity, we applied the gradient projection algorithm to find the optimum locations of the 4 UAVs, and the result is

shown in Fig. 5. For UAVs with an altitude of 300m that doesn't fulfill the concavity, we applied the PSO algorithm to find efficient locations for the 2 UAVs, and the result is shown in Fig. 6.

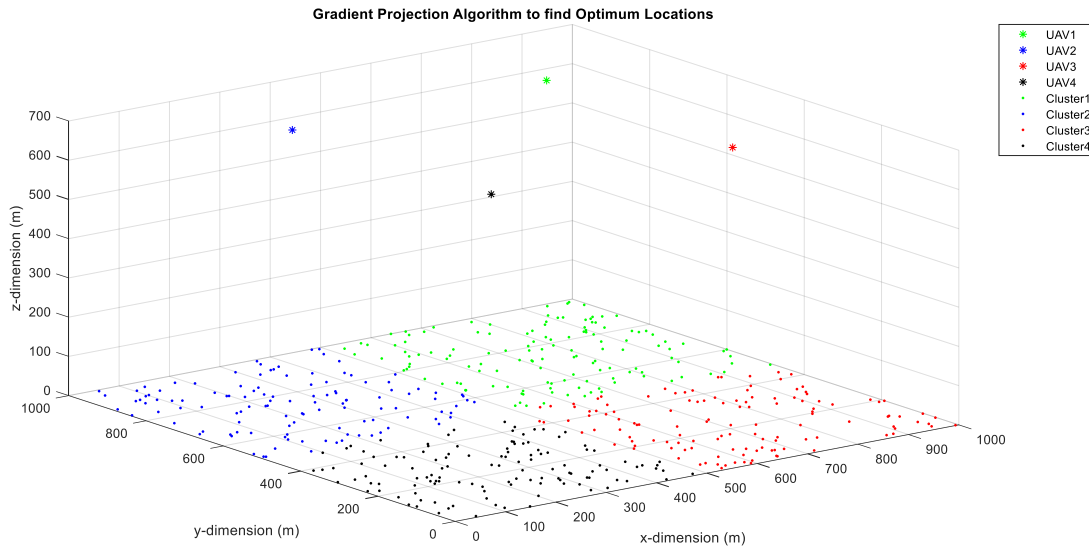


Fig. 5: Applying gradient projection algorithm to uniform distributed users

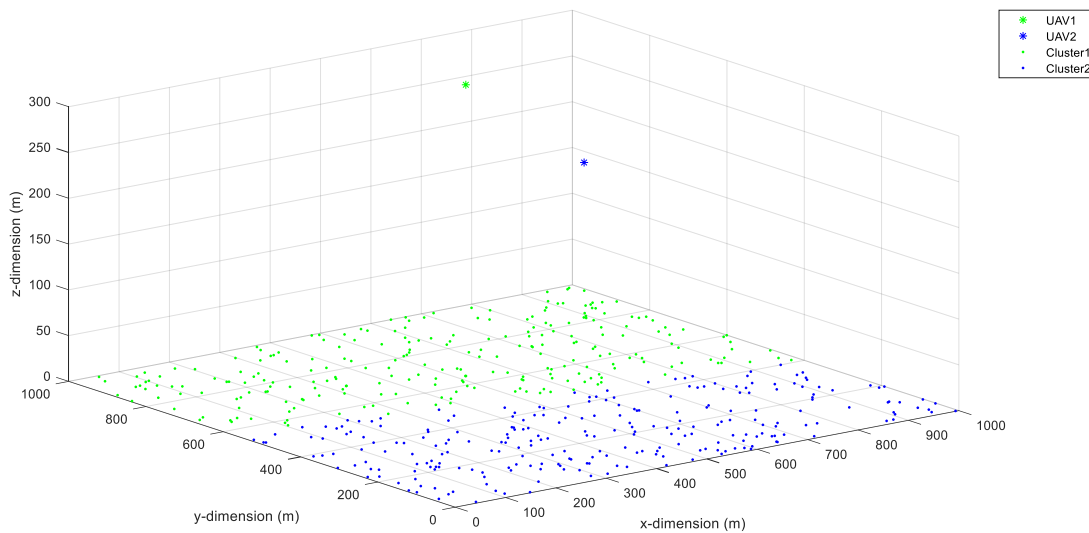


Fig. 6: Applying PSO algorithm to uniform distributed users

In Tables 2 and 3, we present the 3D locations for multiple UAVs and the lifetime for uplink transmission in each cluster resulted from either the gradient projection algorithm or the PSO algorithm. We found the convergence speed of the GP algorithm equals 97 iterations, while the PSO algorithm equals 42 iterations. We also note that we can find the best

locations with an almost equal number of iterations in all clusters. Then, we compare all the results resulted from our proposed algorithm with another algorithm which is the center projection algorithm that will allocate the UAVs at the center of the coverage region.

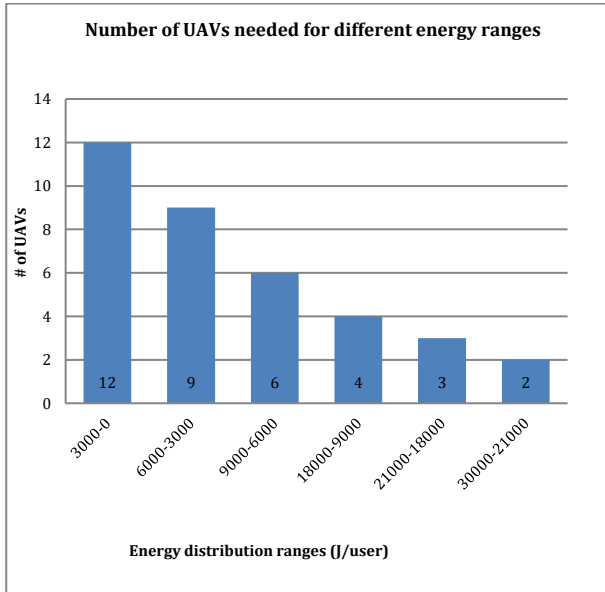
Table 2: Comparison between our proposed approach and center projection algorithm for uniform distributed users at altitude 700m

UAV Index	Gradient Projection Algorithm	Centre Projection Algorithm
1	(753.0632,744.7914,700) m 240710 sec.	(501,501,700) m 200630 sec.
2	(244.8255,740.4361,700) m 213380 sec.	(499,501,700) m 176450 sec.
3	(728.0475,230.7943,700) m 227590 sec.	(499,499,700) m 190120 sec.
4	(246.7610,228.2753,700) m 220260 sec.	(501,499,700) m 177700 sec.

Table 3: Comparison between our proposed approach and center projection algorithm for uniform distributed users at altitude 300m

UAV Index	PSO Algorithm	Centre Projection Algorithm
1	(580.5432,729.0515,300) m 1429900 sec.	(501,499,300) m 1149900 sec.
2	(429.9059,226.7083,300) m 1463600 sec.	(499,501,300) m 1080700 sec.

In Fig. 7, we show the number of UAVs needed for fulfilling all the constraints in 6 according to the range of residual energies distributed among wireless devices of users. We note that the number of UAVs decreases linearly when the residual energies increase.

**Fig. 7:** The number of UAVs needed for different residual energy in a uniform distribution manner

5.2. Non-uniform distributed users

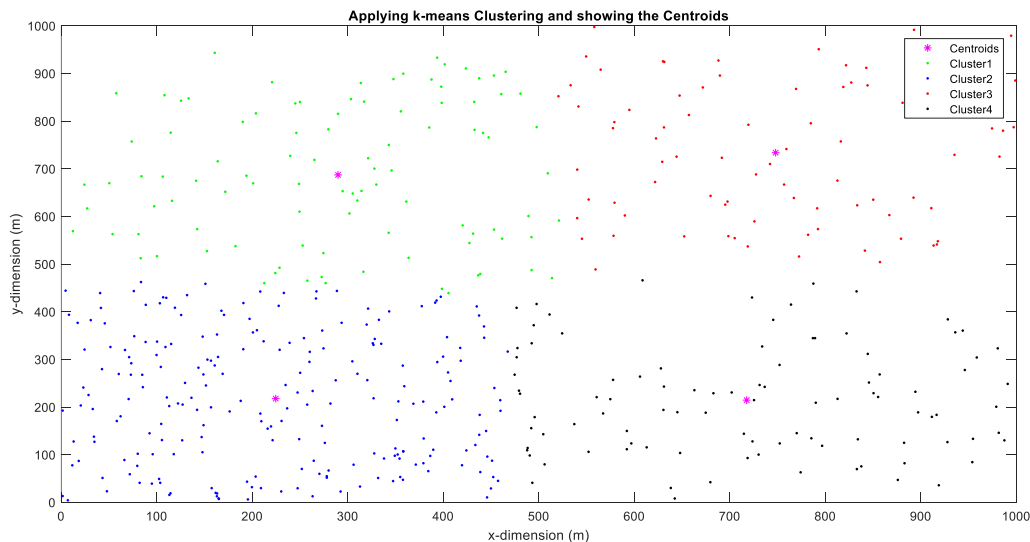
Here, we assume that the users distributed non-uniformly during disaster situations. For non-uniform distribution, we test our proposed algorithm to find the suitable number of UAVs to serve the region in order to achieve maximum T considering the given constraints in 6.

Firstly, we applied the k-means clustering algorithm, we found the best number of clusters for the given simulation parameters, which equal 4 clusters assuming the minimum allowable altitude is 850m and only 2 clusters when we put the UAVs at 300m altitudes. See Fig. 8 that shows the resulted clusters in the case of non-uniform distributed users.

After applying the k-means algorithm, we applied either GP or PSO algorithms. For UAVs that their altitude has fulfilled the concavity, we applied the gradient projection algorithm to find the optimum locations of the 4 UAVs, the result is shown in Fig. 9. For UAVs that their altitude has not fulfilled the concavity, we applied the PSO algorithm to find efficient locations for the 2 UAVs, the result is shown in Fig. 10.

In Tables 4 and 5, we present the 3D locations for multiple UAVs and the lifetime for uplink transmission in each cluster resulted from either the GP algorithm or the PSO algorithm. We found the convergence speed of the GP algorithm equals 97 iterations, while the PSO algorithm equals 51 iterations. But here we note that we can find the best locations in some clusters before others. We compare all the results resulted from our proposed algorithm with another algorithm which is the center projection algorithm that will allocate the UAVs at the center of the coverage region.

In Fig. 11, we show the number of UAVs needed for fulfilling all the constraints in 6 according to the range of residual energies distributed among wireless devices of users. We note that the number of UAVs decreases exponentially when the residual energies increase uniformly.



(a)

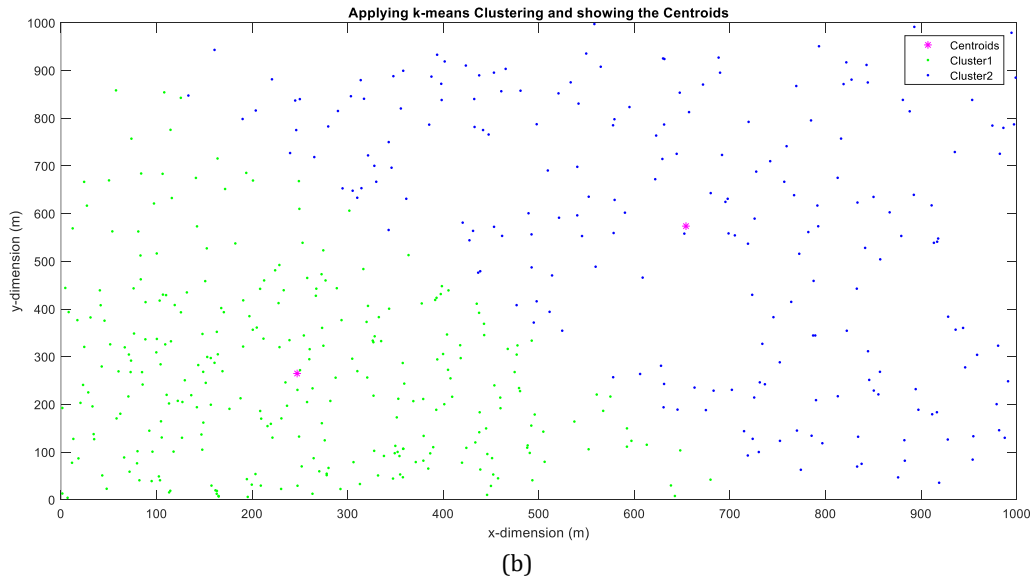


Fig. 8: K-means clustering applied to cluster non-uniform distributed users at (a) $z_{\min}=850\text{m}$, (b) $z_{\min}=300\text{m}$

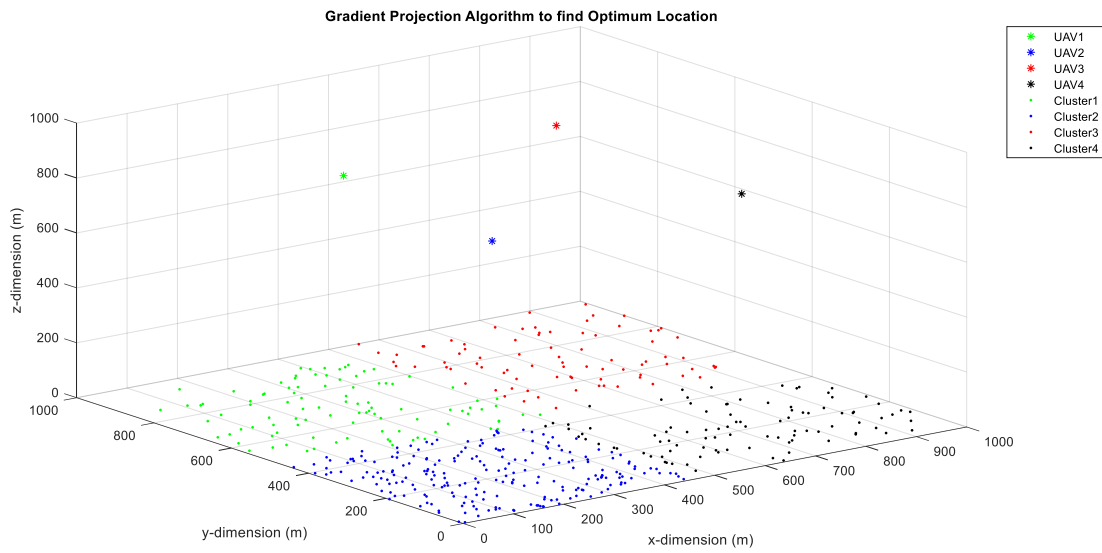


Fig. 9: Applying gradient projection algorithm to non-uniform distributed users

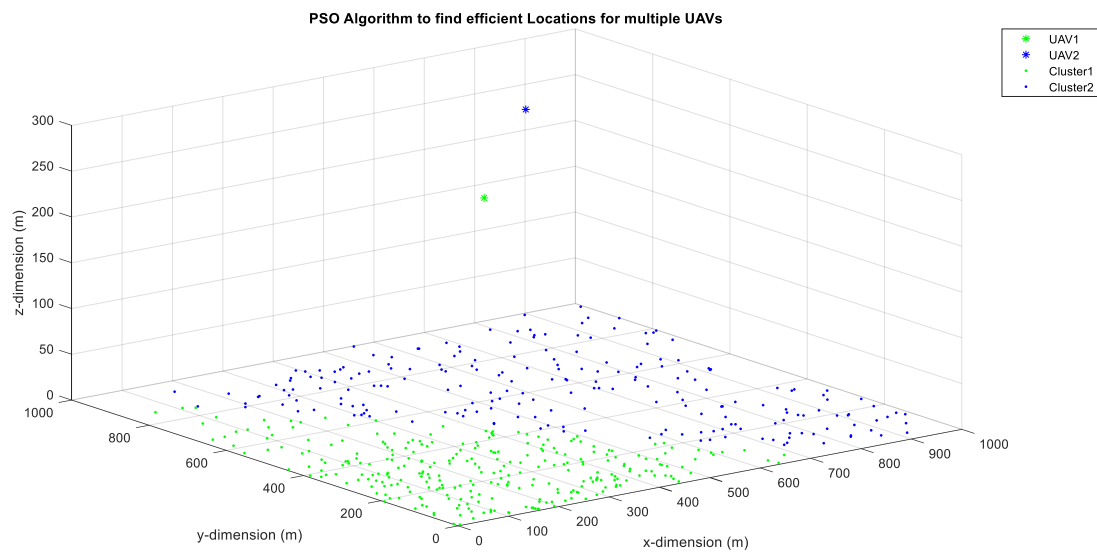


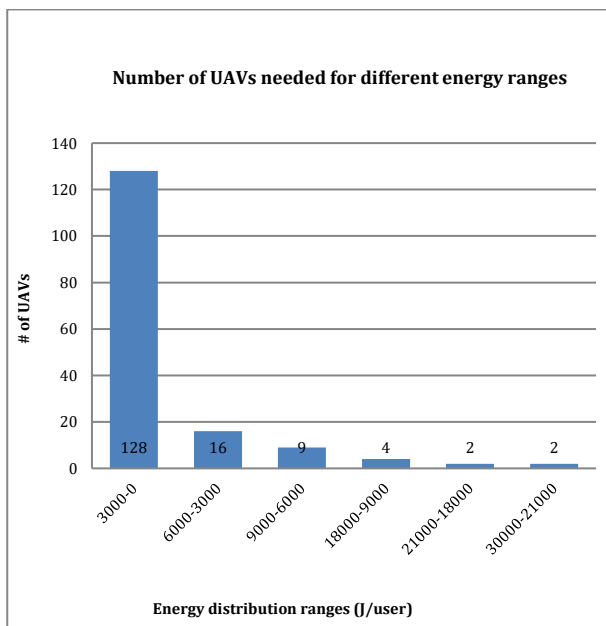
Fig. 10: Applying PSO algorithm to non-uniform distributed users

Table 4: Comparison between our proposed approach and center projection algorithm for non-uniform distributed users at altitude 850m

UAV Index	Gradient Projection Algorithm	Center Projection Algorithm
1	(289.8006,687.1417,850) m 126000 sec.	(501,501,850) m 114950 sec.
2	(224.5817,217.6537,850) m 284280 sec.	(499,501,850) m 238180 sec.
3	(748.0082,733.6825,850) m 106200 sec.	(499,499,850) m 89782 sec.
4	(717.6794,214.4156,850) m 118050 sec.	(501,499,850) m 101810 sec.

Table 5: Comparison between our proposed approach and center projection algorithm for non-uniform distributed users at altitude 300m

UAV index	PSO Algorithm	Center Projection Algorithm
1	(237.1539,241.7779,300) m 2062000 sec.	(501,499,300) m 1195700 sec.
2	(628.8436,644.5659,300) m 1126500 sec.	(499,501,300) m 1005800 sec.

**Fig. 11:** The number of UAVs needed for different residual energy in a non-uniform distribution manner

6. Conclusion

In this paper, the problem of efficient or even optimal 3D placements for multiple UAVs in an mm-wave network in case of disaster situations is studied. First, we formulate the problem which finds the optimal placements for multiple UAVs, where we aim to allocate the placements of multiple UAVs in order to have a maximum sum of uplink transmissions' time durations. To achieve this, we proposed an algorithm to find the efficient or even optimal UAVs' locations. Simulation results are produced to verify the efficiency of our proposed algorithm. In the results, we can see the lifetime enhancement in our algorithm compared with the center projection algorithm. Also, we note that when users' distribution is uniform, the number of UAVs decreases linearly with increasing the energy of the users. On the other hand, when users' distribution is non-uniform, the number of UAVs decreases exponentially with increasing the energy of the users.

Compliance with ethical standards

Conflict of interest

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