electronics

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Energy-Efficient Resource Allocation in Aerial Base Stations

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Abstract: Drones, or unmanned aerial vehicles, can be used as air base stations (UAV-BSs) for telecommunications. They prove useful in situations where the network is overloaded or unavailable due to natural disasters or maintenance work. UAV-BSs grant access to user/IoTs sensors on the ground, but their electromagnetic signals may suffer losses because of their dynamic capacity to provide access at different altitudes. These losses lead to transmission impairments, such as attenuation, fading, and distortion. To overcome these issues and improve signal quality, the UAV-BS position must be optimized. However, finding the optimal placement is a challenge, and a wide range of strategies employing different approaches have been adopted. In this study, we proposed a 3D positioning strategy for UAV-BSs that serves the maximum number of users with the smallest number of UAV-BSs. Results showed that the proposed heuristic could find the best position and altitude for the UAV-BSs, provide network access for mobile user/IoTs (Internet of things) sensors, maximize the number of devices connected to the UAV-BSs, and guarantee a minimum throughput for users. The proposed heuristic not only performs well in terms of coverage and performance, but is also more energy-efficient than other algorithms found in the literature.

Keywords: UAV-BS; telecommunications; networks; allocation; energy-efficient

Citation: Silva, W.R.S.e.; Torres, R.H.; Cardoso, D.L. Energy-Efficient Resource Allocation in Aerial Base Stations. *Electronics* **2023**, *12*, 4478. https://doi.org/10.3390/electronics12214478

Academic Editors: Ivan Ganchev, Máirtín O'Droma and Zhanlin Ji

Received: 21 August 2023
Revised: 21 September 2023
Accepted: 22 September 2023
Published: 31 October 2023

1. Introduction

UAV-BSs can be deployed to provide wireless connectivity to ground-based devices, since they are able to provide access to users or IoTs objects at different altitudes. UAVs offer a useful means of ensuring the flexible deployment of air stations [1]. UAVs are mobile and dynamic access points that are deployed when ground base stations are overloaded or if there are temporary power outages caused by disasters or excessive user flow at certain times. The authors in [2–5] address the way air base stations can provide access to users on the ground as an alternative to traditional networks. UAVs can help ground-based radio stations provide signal coverage and achieve high data rates [6], especially in situations where this excessive demand occurs in a way that is quite difficult to predict, as can be seen in Figure 1.

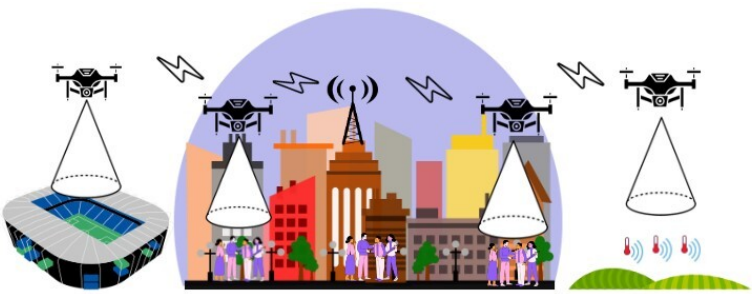

Figure 1. UAV-BS positioned at different altitudes to improve signal quality for user/IoTs sensors on the ground.

The UAV-BS, equipped with a directional antenna, provides wireless coverage for a particular area. The signal propagation includes both the line-of-sight and nonline-of-sight for ground-based users [7]. However, this electromagnetic propagation suffers losses along the path, thereby resulting in attenuation, fading, and distortion problems. It is, therefore, essential to find the ideal position and altitude for coverage, thereby ensuring at least a minimum quality of service (QoS) for the users on the ground.

As presented in [8], the transmission range of a UAV-BS depends on its altitude. However, finding the best position and altitude for the UAV-BS remains a challenging task, as these factors have a direct effect on the signal coverage and data rate perceived by the ground users [9].

This paper proposes a new way of allocating air stations to serve mobile user/IoTs sensors during disaster situations. It optimizes the number of users served while relying on the minimum number of UAV-BSs. To achieve this, the paper employs a heuristic that finds the best position and altitude for each UAV-BS, thus guaranteeing user service, signal coverage, the quality of service, and energy efficiency. The proposed solution was compared with other strategies discussed in the literature, and the results showed an improvement in energy efficiency due to the better distribution of the UAV-BSs, thereby ensuring better coverage.

The paper is structured as follows: Section II examines related work that supports the proposal, Section III introduces some key concepts used in the model, Section IV shows how the heuristic is used and examines the results achieved, and Section V concludes the study and makes recommendations for future work in the field.

2. Related Work

UAVs are becoming increasingly popular in the telecommunications industry due to their flexible deployment. One suggestion made by [10] is to use multiple mobile air stations to cover large areas while reducing the number of UAVs required. Other applications, such as the work of [11], rely on directional antennas to check signal coverage and study the connectivity in networks covered only by mobile air stations.

The study carried out in [12] explored the potential that UAVs have for IoTs data collection and path optimization. To achieve this, the researchers employed a reinforcement learning technique to determine the most efficient route and transfer rate in a given environment. Additionally, in another study [13], a cooperative approach was adopted to integrate UAVs with traditional networks. Reinforcement learning, as a part of a machine learning technique, was employed by the researchers to enhance the range and coverage of the signal transmission.

The paper [14] discusses the use of UAV-BSs in natural disaster areas. The researchers validated their hypothesis by means of computer simulation tools and methods that employed benchmark databases to evaluate their algorithms for signal coverage.

Energy optimization is essential for the navigation of UAVs, since they only operate on batteries and, in most cases, do not have access to charging stations. Another study conducted in [15] studied 3D trajectory and motion. The work examined the speed and acceleration of the UAV, as well as its curvature along a path. Safety restrictions were guaranteed by requiring a minimum safety distance to avoid obstacles.

The paper carried out in [16] provides a new proposal to plan energy-efficient and collision-free paths for a quadcopter UAV by calculating the best route with the aid of reinforcement algorithms. Another study [17], recommends deploying them in 3D to ensure secure presence-based communications and thus maximize the signal strength and reduce the received signal strength. This can be carried out by using the genetic algorithm (GA) as a basis and adjusting the 3D positions of the UAV-BSs.

In another study, Ref. [18] conducted an analysis of the coverage probability of mobile networks aided by UAVs. The proposed algorithm and Monte Carlo simulations were used to validate the experiments. Finally, the paper by [19] adopted an approach for UAV-BSs using 5G communication systems by means of a metaheuristic algorithm. Here is a summary of the articles that discuss the allocation of UAV-BSs in disaster situations or network overload to assist mobile networks. The values used in this research are shown in Table 1.

Table 1. Literature review.

Paper	Problem	Technique Used
[10]	How to make use of multiple mobile air stations to cover large areas while reducing the number of UAVs	Use of a heuristic algorithm
[11]	Employing directional antennas to check signal coverage	Algorithm proposed
[12]	Using UAVs for IoTs (Internet of Things) data collection	Algorithm proposed
[13]	Adopting a cooperative approach to integrate UAVs	Algorithm proposed
[14]	Using UAVs in a natural disaster area	Fuzzy c-means clustering recommended
[15]	Planning the UAV 3D path and motion	Algorithm proposed
[16]	3D autonomous navigation of UAVs	Algorithm proposed
[17]	3D deployment of UAVs for communications	Algorithm proposed
[18]	A study was conducted for the probability analysis of the coverage of mobile networks assisted by UAV-BSs	Algorithm and Monte Carlo simulations
[19]	How to adopt an approach for the Drone-BS in 5G communications systems	Metaheuristic algorithm

This proposal introduces a novel 3D positioning strategy for unmanned aerial vehicles that provides better coverage for mobile user/IoTs sensors based on the quality of service. It includes (i) a method for positioning UAV base stations, (ii) an analysis of the flight time performance of UAV-BSs, and (iii) an energy-efficient algorithm that optimizes the use of UAV-BSs in mobile coverage. The algorithm ensured that the largest number of users could be served by using the smallest number of UAV-BSs, thus outperforming other tested strategies.

3. Network Design Assumptions

In this section, there is an examination of the strategy employed, as well as a detailed account of the stages of the research methodology.

3.1. Network Assumptions

Mobile communications make use of radio channel wave patterns over a wide range of frequencies. This system assists mobile network planning and coverage, as well as quickly predicts its performance. Some parameters related to the study of UAV-BSs have been taken into account. This is illustrated by the directional antenna in the diagram shown below; see Figure 2.

This work employed the propagation model, which is listed in the International Telecommunication Union (ITU-R) [20–24]. This model is suitable for use in both urban and suburban environments, and it incorporates various parameters for accurate calculations. A general path loss model was used for air-to-ground transmission. The model takes account of the line-of-sight (LoS) and the nonline-of-sight (NLoS), as are described below [25], where f is a variable that represents the carrier frequency, d is a variable that represents a distance (in meters), and c is a constant that represents the speed of light.

$$\mathrm{PL_{LoS}} = 20\log\left(\frac{4\pi f_c d_{ij}}{c}\right) + \eta_{\mathrm{LoS}}\mathrm{PL_{NLoS}} = 20\log\left(\frac{4\pi f_c d_{ij}}{c}\right) + \eta_{\mathrm{NLoS}} \quad (1)$$

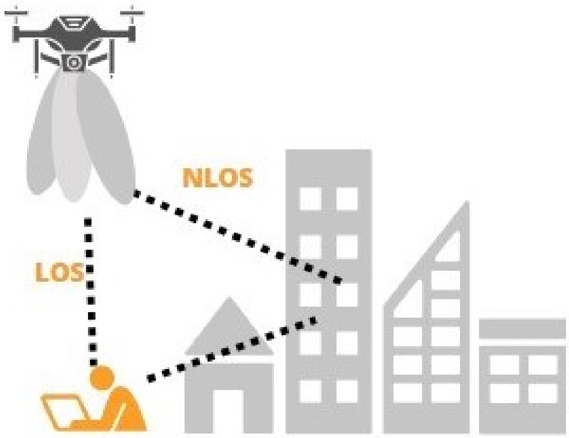

Figure 2. LOS and NLOS.

The equation below expresses the formula for calculating the distance from the user to the UAV-BS, where D is the distance between two points. The point x, x_i represents the coordinates of the first point. The point y, y_i represents the coordinates of the second point [26].

$$D_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{2}$$

The UAV-BS adopts a frequency division multiple access (FDMA) technique to serve terrestrial user/IoTs sensors. FDMA allocates several frequency bands to users, and each user has its own communication channel. The achievable user rate is expressed below, where B is the allocated bandwidth per user, Pu is the power transmitted by the UAV-BS, N_0 is the power, and G is the gain of the directional antenna [27].

$$R = B \log_2\left(1 + \frac{P_u G}{L N_0 B}\right) \tag{3}$$

In Brazil, UAV flights are regulated by the National Civil Aviation Agency (ANAC), which imposes standards to guarantee public safety. The regulations stipulate that the use of a UAV-BS should be between 30 and 120 m high and at a distance of 5.4 km from an airfield or airport [28].

3.2. Formulation of the Problem

Finding the transmitter antenna placement for optimum performance, or, in this case, the vertical and horizontal placement of the UAV-BS, is described as an optimization problem because of its complexity. Bearing in mind that the number of UAV-BSs is limited for financial reasons and that each drone has a flight cost, it is necessary to find a solution that solves the problem by reducing their use. The problem at hand is regarded as being nonconvex, which means it can have multiple local optimal solutions and is classified as NP-Hard [29–31].

The main goal of this work is to develop a heuristic that can solve the UAV-BS positioning problem. As a heuristic, it is capable of finding suboptimal solutions in an acceptable computational time frame with processing capacity. The mathematical model that can reduce the number of UAV-BSs with regard to the users on the ground is shown below:

Problem: Minimization the number of UAV-BSs.

Variables:

x_i Number of UAV-BSs to be installed in sector i $\quad (i = 1, 2, \ldots, n)$

h_i Altitude of UAV-BSs in sector i $\quad (i = 1, 2, \ldots, n)$

Objective Function:

$$\text{Minimize } Z = \sum_{i=1}^{n} x_i$$

Subject to the following:

$$\begin{aligned}
&\sum_{i=1}^{n} (N_{uj} \cdot x_i) \leq C_t \quad \text{for each sector } j = 1, 2, \ldots, n \\
&x_i \geq 1 \quad \text{for } i = 1, 2, \ldots, \quad \forall n \in N \\
&h_i \geq 30 \quad \text{for } i = 1, 2, \ldots, \quad \forall n \in N \\
&h_i \leq 100 \quad \text{for } i = 1, 2, \ldots, \quad \forall n \in N \\
&x_i, h_i \geq 0 \quad \text{for } i = 1, 2, \ldots, \quad \forall n \in N
\end{aligned}$$

where:

- Z is the objective function that seeks to minimize the total number of UAV-BSs.
- x_i represents the number of UAV-BSs to be installed in sector i.
- h_i represents the altitude of the UAV-BSs in sector i.
- n is the total number of sectors.
- N_{uj} is the number of users in sector j.
- C_t is the capacity of a UAV-BS, i.e., the maximum number of users that a UAV-BS can serve.

The algorithm checks the minimum data rate required by each user in the cluster. This value ensures the QoS for all the users assigned by a UAV-BS.

Reducing the number of UAV-BSs is essential for energy conservation. Finding a solution that can address the problem with the minimum available resources will have a direct impact on global energy efficiency. If only the requested amount is provided, the resources will not be wasted.

3.3. Proposed Heuristic

The proposed heuristic is a method that determinates the minimum number of UAV-BSs required and the altitude at which each of them should operate to serve the users on the ground efficiently. It performs multiple iterations by gradually increasing the number of UAV-BSs so that it can find an optimal solution. The heuristic stops when it has overcome all the constraints and is able to assign a UAV-BS to the users.

The heuristic involves four stages : (1) the clustering of users using k-means clustering, (2) the allocation of users to the nearest UAV-BS and the verification of its quality of service, (3) the evaluation of the best solution based on the number of users served, and (4) granting access to ground users, as are shown in Figure 3.

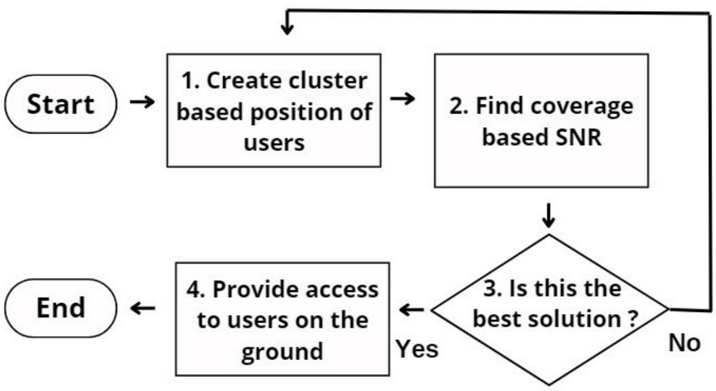

Figure 3. Stages of the proposed heuristic.

These steps are outlined in the Algorithm 1 described below.

Several parameters are used as inputs, for example, these include the following: the number of users, the number of clusters, Tx power, Rx power, channel, bandwidth, resource blocks, and NRs.

Algorithm 1 Allocation of UAV-BSs

1: input_users$(x, y, dr, prb, cqi, sinr, vel, prx, distance)$
2: input_uavbs$(x, y, rb, fr, band, ptx, cob, h, channel)$
3: best, bestAtual = 0
4: solution = 0
5: rounds = 300
6: Create Position User
7: User=randon(x,y)
8: **while** $(solution <= rounds)$ **do**
9: create a cluster for position UAV center of the cluster
10: cluster=kmeans(Users/IoT sensors)
11: Calculate maximum distance users
12: **for** i = 1 to *cluster* **do**
13: MaxDistance = Maximum Distance all Users/IoT sensors to Cluster
14: **end for**
15: try to allocate in each cluster
16: **for** i = 1 to *UavBS* **do**
17: **for** j = 1 to *Users* **do**
18: **if** $(DistUser <= DistMaxUAV)$ and $(sinrUser < sirnMaxUAV)$ and $(interference < Value)$ **then**
19: allocate user in the UAV-BS
20: $UAV_i = \{user_j, user_j, \ldots, user_n\}$
21: **end if**
22: **end for**
23: **end for**
24: totalUser = sum(UsersAllocationNetwork)
25: **if** $(totalUser >= best)$ **then**
26: $UavUser_j = \{user_1, user_2, \ldots, user_n\}$
27: best = totalUser
28: **end if**
29: $rounds$=$rounds$ + 1
30: **end while**
31: Plot solution search

The UAV-BS positioning algorithm involves clustering users to determine the best placement. In this work, the k-means algorithm was employed for clustering. This algorithm is a widely used machine learning technique for grouping data points into classes. It is popular because of its simplicity and computational efficiency.

When using k-means, it is necessary to randomly choose k centroids, where k is the number of clusters or datasets. After this, the algorithm tries to find the center of a cluster. The minimum number of UAV-BSs is employed to guarantee the initial coverage of users on the ground.

Once the clusters are formed, the ideal altitude, coverage radius, and signal strength are calculated for each group. If the solution obtained is not acceptable, a loop is executed, which is called Step 01, and this increments the number of clusters. This is repeated until the constraints of the problem are satisfied.

With regard to the interference and signal level, the algorithm in question makes calculations when it is looking for the ideal position for mobile coverage. It even uses two variables (signal strength and intraUAV interference) to allocate an available drone for users on the ground, and they are both calculated during the users' allocation phase for the UAV-BS, as is pointed out in line 18 of Algorithm 1.

When it comes to collisions, this research focused on the ideal positioning of UAV-BSs while keeping the focus on the allocation of the UAV-BSs, and it was assumed that they already had advanced mechanisms to detect collisions, such as computer vision, which is capable of carrying out maneuvers and avoiding possible obstacles by deviating from the normal path. The algorithm proceeds until it finds a solution that satisfies the objective function.

The following strategy was used to divide the users into different groups. Initially, they were separated into sets. The set of mobile user/IoTs sensors is arranged in the equation u = {1, 2..u }, the clustering set in g = {1, 2..g }, and the drone set in d = {1, 2..d }. Once the users have been grouped, they can be served by the nearest UAV-BS.

The altitude was adjusted according to the power received by the users and the coverage area of each cluster. This ensures that the signal quality is maintained. The algorithm evaluates each user's signal from UAV-BSs within each cluster, and this is repeated for each cluster. If the minimum QoS is achieved, the optimum altitude of the UAV-BS can be found.

Initially, the users started out with a defined lat/log position and their required data rate. After this, the UAV-BSs were configured with suitable parameters for the band, frequency, altitude, and available resources. Then, the k-means cluster set the altitude, defined the coverage and distance, and positioned itself in the center. Following this, the QoS was evaluated to ensure that the maximum number of users could be serviced by the drone. Finally, the solution found was then used, as is shown in Figure 4.

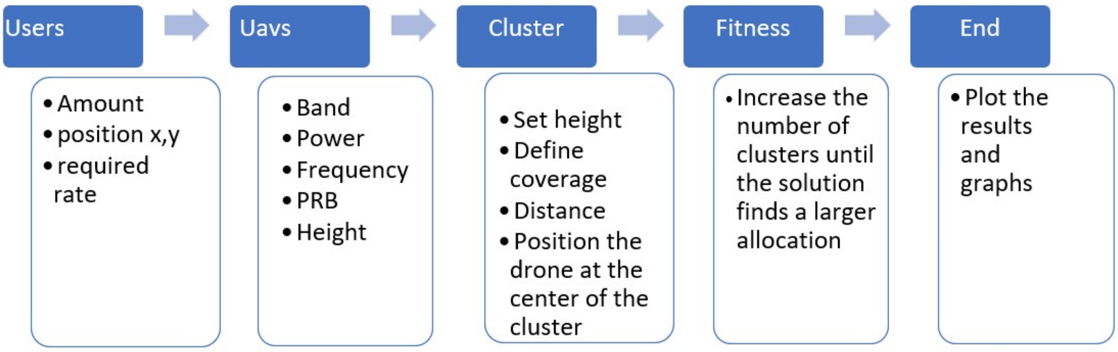

Figure 4. Steps of the simulation.

Three strategies were assessed to determine the most effective way to cover an area with landless users: (a) [32], (b) [33], and (c) the Dynamic Strategy. Each strategy relies on the positioning, altitude, and coverage radius of the drone.

The first strategy—(a) Random—involves a random altitude and coverage radius for the UAV-BS. The second strategy—(b) Fixed—requires the UAV-BS to maintain a pre-configured altitude and coverage radius. In contrast to the first two strategies, (c) the Dynamic Strategy enables the altitude and coverage radius of the UAV-BS to be adjusted in a dynamic way. This allows the drone to be optimally positioned in relation to the users on the ground.

4. Results and Discussion

The simulation was repeated 40 times for statistical purposes, with random seeds, and each simulation took 100 s. It was carried out in accordance with the regulations, which stipulate that the UAV-BS should be used between an altitude of 30 and 120 m. The simulations were carried out in Matlab®2022 and Pydrone®2022.

4.1. Scenario

The chosen scenario was based on a natural disaster that causes a failure in the base station and prevents mobile user/IoTs sensors from being able to connect to the network. Users undertake the simulation on the basis of a uniform distribution [34], with network requirements of 1 to 3 Mbps. A total of 100 stationary users were selected in the specified geographical area of 1000 × 1000 m. The network used was the LTE standard, and the UAV-BSs had a bandwidth of 20 MHz, with resource blocks limited to 100. Each drone could connect to a macrocell with 40 Mbps. All the parameters are shown in Table 2.

Table 2. Simulation parameters.

Parameter	Description	Value
Hmin	Initial altitude of the UAV	30 m
Bw	Bandwidth of the UAV	20 MHz
Ptr	UAV tranmission power	23 dbm
Cmin	Minimum channel capacity	3 Mbps
UAVtUs	PL Model	Los e Nlos
Los	*los*	1.3 dB
Nlos	*nlos*	23 dB
BS	Base station	1
Sc	Scenarios	3
Us	Users	100

A determining factor for energy saving is the flight altitude. Wind currents at different altitudes incur higher stabilization costs, thus causing higher energy prices [35–37]. There are different laws for drone flights in different countries. The values used in this research are shown in Table 3.

Table 3. UAV-BS parameters.

Parameter	Description
Weight	2 kg
Battery	5200 mAh 14.8 V
Electric motors	880 kV (×4)
Max speed	10 km/h
Max altitude	150 m
Total flying time	30 min

A different strategy for user allocation was adopted for each simulation, and the distributions are shown in Table 4. In each strategy, the number of UAV-BSs was chosen and positioned in accordance with its parameters. At the end of the simulation, the final positions of the UAV-BSs and users were displayed.

Table 4. Allocation parameters of the users.

Status	User	Data Rate	PRB	CQI	SINR	PRX	UAVBS	LAT	LOG
On	1	409,600	5	4	2.61	87	uav 3	4.54	7.10
On	2	409,600	4	3	4.54	85	uav 3	4.44	7.54
On	3	409,600	5	5	3.32	84	uav 3	4.69	7.12
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
Off	99	409,600	0	0	0	0	0	7.42	10.18
Off	100	409,600	0	0	0	0	0	7.54	10.89

4.2. Results—Allocation of UAV-BSs

The ultimate allocation for each approach adopted is showcased in Figure 5. The altitude and average coverage radius of the UAV-BS are clearly defined as follows: (a) Random—an altitude of 150 m and a radius of 150 m; (b) Fixed—an altitude of 200 m and a coverage radius of 200 m; and, lastly, (c) Dynamic—an average altitude of 130 m and a radius of 350 m.

On the basis of the analysis, it is clear that the Dynamic Strategy (c) was more efficient in its use of the available resources, since it was able to deploy the minimum number of

UAV-BSs to serve the maximum number of users. This is owing to the capacity of the algorithm to determine the optimal positioning and altitude, and this results in a faster and more efficient performance. As a result, this strategy ensured network accessibility for the mobile user while being the most energy-efficient option available.

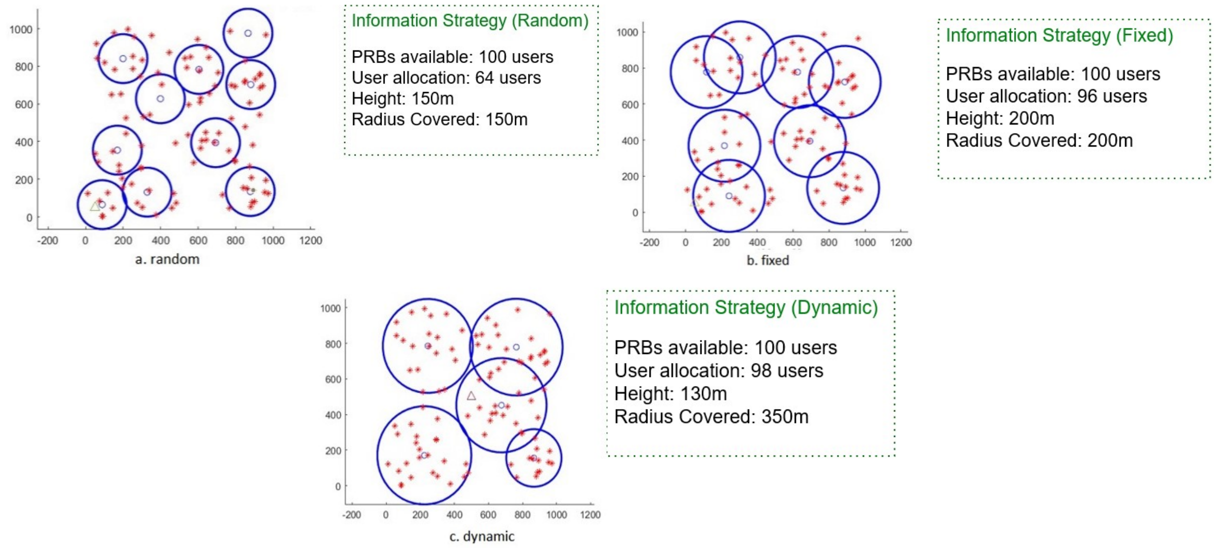

Figure 5. Number of clusters allocated in each strategy. In (**a**), 10 clusters were allocated with random altitudes and coverage. In (**b**), 8 clusters were allocated with fixed altitudes and coverage, and in (**c**), 5 clusters were allocated with dynamic altitudes and coverage.

The best 'fitness' obtained in each algorithm is shown below, with red arrows highlighting the optimal solution. In the Random approach, 64 users were covered in iteration 10 using 10 UAV-BSs, and 36 users remained uncovered. In the Fixed approach, 96 users were covered in iteration 9 using nine UAV-BSs, and 4 users remained uncovered. Finally, the Dynamic approach covered 98 users in iteration 5, leaving only 2 users uncovered, with the help of five drones. This shows that the recommended algorithm was able to find the optimal solution more efficiently, as is demonstrated in Figure 6.

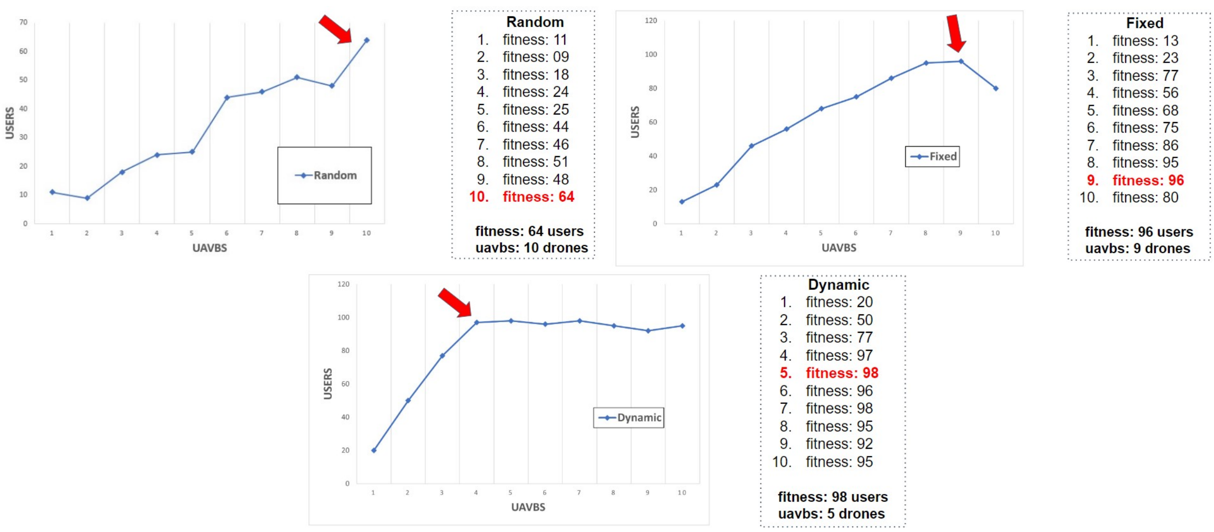

Figure 6. Algorithm convergence to find the best fitness. The arrow shows the moment when the algorithm finds the best coverage

4.3. Results—Heuristic Performance

After the number of users served had been calculated, it became clear that the Random strategy was the least effective, as it failed to allocate the required number of users. In contrast, the Fixed strategy was almost able to allocate the maximum number of users, but it required 10 iterations to do so. The most successful strategy was the Dynamic Strategy, which not only allocated the maximum number of users, but did so in the shortest computational time. Among the Dynamic, Fixed, and Random strategies, the Dynamic system provided access to 98 users, while the Fixed and Random strategies only provided access to 96 and 64 users, respectively. Thus, the Dynamic Strategy was able to serve more users than the other strategies, as can be seen in Figure 7.

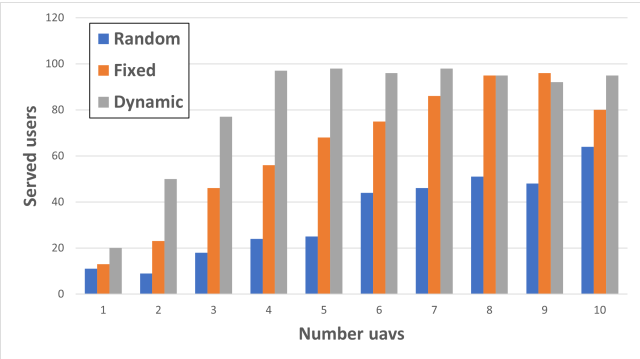

Figure 7. The number of users served by UAV-BS strategies.

An assessment was also made of the efficiency of the algorithm in finding the optimal solution. The solutions demonstrated a resolution of O(log N). Note that the computational time for the (a) Random, (b) Fixed, and (c) Dynamic strategies were poor, good, and excellent, respectively. This is illustrated in Figure 8.

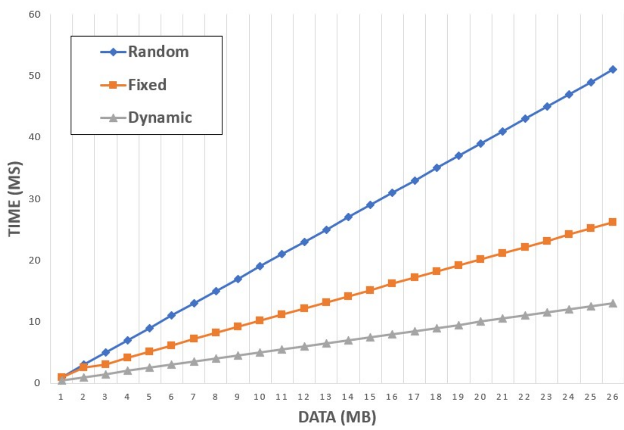

Figure 8. Algorithm performance results.

Another comparison was made to evaluate the average user throughput. The Dynamic Strategy (c) outperformed the Fixed (b) and Random (a) positioning, as is shown in Figure 9.

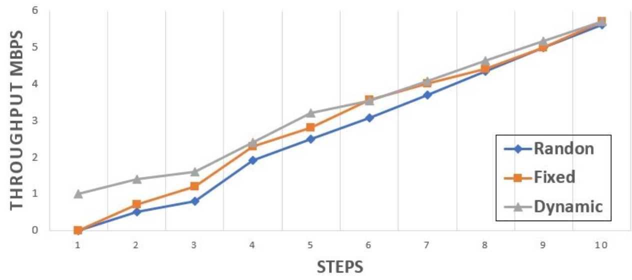

Figure 9. Throughput performance results.

The flight data provides information about the altitude and battery energy consumption of each UAV-BS. There were three types of positions for the UAV-BSs: (a) random positions at different altitudes, (b) fixed positions at specific altitudes, and (c) dynamic positions that placed each UAV-BS at an ideal altitude; note that the UAV-BSs flew lower to avoid stronger gap winds that could destabilize them. The strategy of keeping the UAV-BS closer to the ground saved energy by avoiding large wind gusts and reducing the amount of energy needed to maintain stability in the air. This is illustrated in Figures 10 and 11.

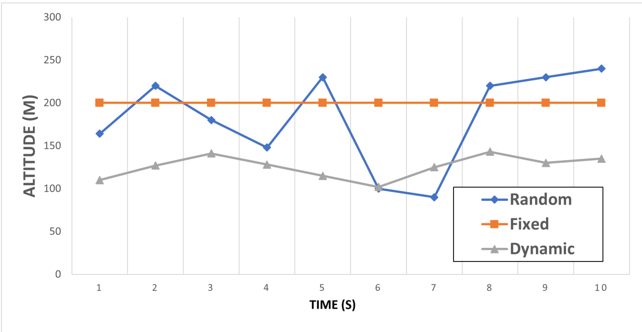

Figure 10. Energy consumption and altitude of each approach.

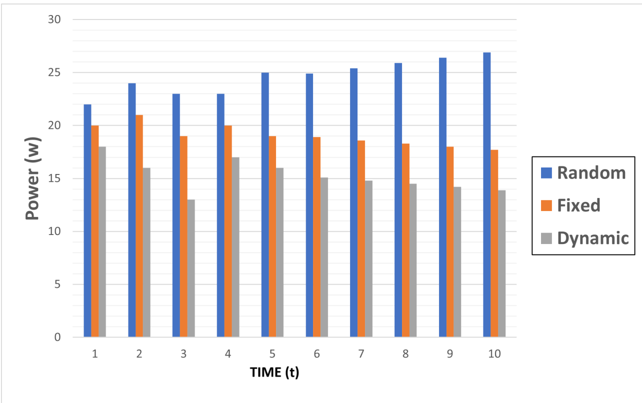

Figure 11. Energy consumption for different allocations.

4.4. Results—Comparison of Energy Efficiency

Energy efficiency is a crucial factor in UAV-BS operations, and an effective way to achieve it is by reducing the number of UAV-BSs deployed without compromising mobile coverage. The challenge is how to optimize the use of limited resources while ensuring a high level of service to the users on the ground. This matter has been discussed in a previous study by [38].

The Dynamic Strategy was compared with [38] by means of the same parameters such as the area, power, number of UAV-BSs, number of users, bandwidth, signal-to-noise ratio, and frequency. Ref. [38] employed the gray wolf algorithm to position the UAV-BSs in a way that assisted the base station. The input parameters used in their simulations can be found in Table 5.

Table 5. Parameters from [38].

Parameters	Values
fc	28 GHz
hmin $\leq$ h $\leq$ hmax	1000 $\leq$ h $\leq$ 3000 m
M (number of drone-BSs)	10
N (number of users)	200
pt	30 dBm
$SINR$	5 dBm
B	20 MHz

The results obtained by [38] showed that a minimum number of five UAV-BSs was required to cover the studied area and 76% of the users served. The Dynamic Strategy showed that four UAV-BSs were needed to cover the studied area and all 200 users served, thus reaching a service of 100%. The results can be seen in Table 6.

Table 6. A comparison of performance.

	[38]	Current Proposal
Minimum number UAV-BSs	5	4
Users served	165	200

The positioning of the UAV-BSs can be seen in Figure 12. Note that the entire area was covered by the UAV-BSs, and all the users were served. This is because the algorithm optimizes the individual altitude of each drone so that it can ensure an ideal height that is capable of providing service to the users on the ground. Thus, the proposed solution is more efficient, as it can serve all of the users and also reduce the number of UAV-BSs. The results of the optimized positioning, as well as the altitude found for each drone, are shown in Table 7.

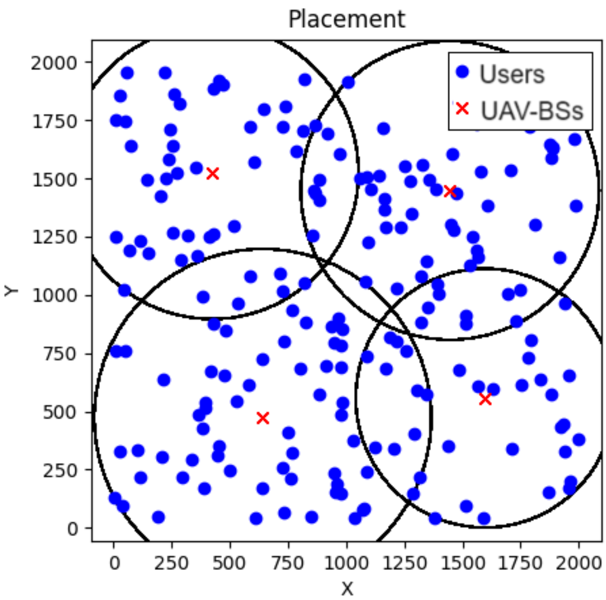

Figure 12. Energy efficiency of UAV-BS Dynamic Strategy.

Table 7. Current proposal.

Drone	Amount of Users	Altitude
1	53	1.888
2	43	1.667
3	58	2.173
4	46	1.923

4.5. Results—Dynamic 3D UAV-BS Placements

The algorithm positioned the UAV-BSs horizontally, and 2D deployment of the allocation can be seen in Figure 13.

The Dynamic proposal was used to group the mobile user/IoTs sensors, which allowed the positioning of the UAV-BSs. The algorithm found five clusters. There was a central BS that provided the backhaul for the UAVs. Each UAV-BS provided a wireless signal to the distributed users, as can be seen in Figure 14.

In these scenarios, it should be noted that there was a three-dimensional movement of the UAV-BSs for the mobile user/IoTs sensors. Each UAV-BS was designated a number and color, and each was located at the center of its respective user group. By flying at a particular altitude and radius, as well as by employing a specific average power signal, the UAV-BSs optimized network resources to enhance user satisfaction while reducing resource consumption. For further details, please refer to Figure 15.

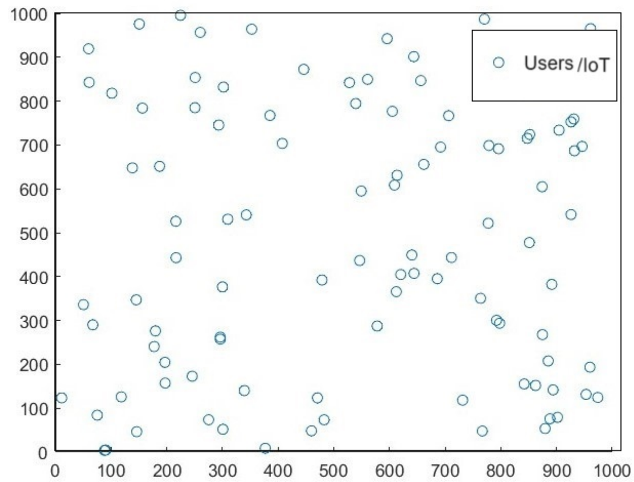

Figure 13. Mobile user/IoTs sensors.

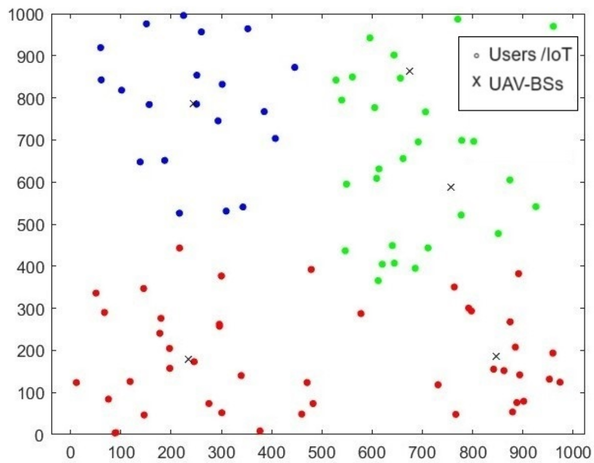

Figure 14. Clustering of mobile user/IoTs sensors.

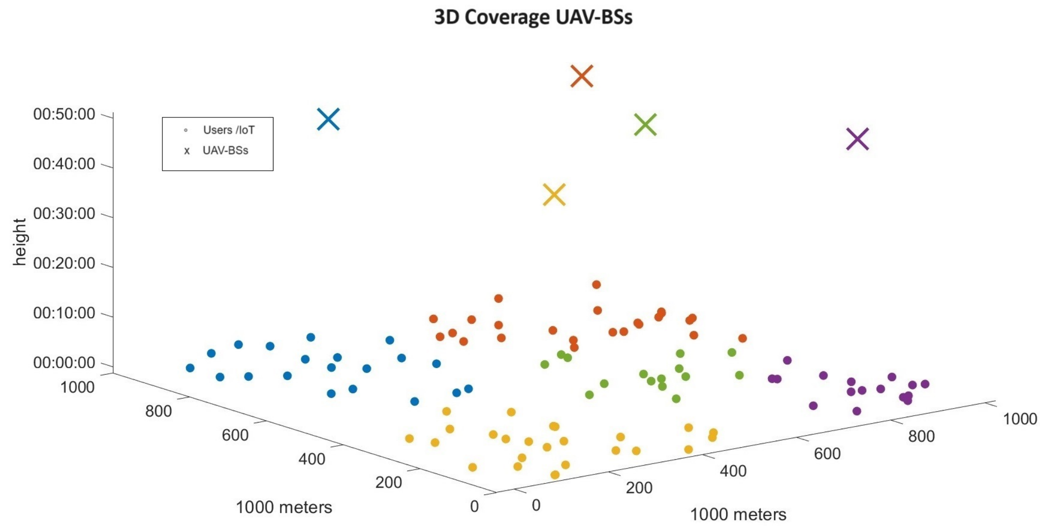

Figure 15. 3D allocation with 5 UAV-BSs.

5. Conclusions

This paper has put forward a scheme for the allocation of UAV-BSs with the aim of achieving greater energy efficiency. The results demonstrate that the proposed algorithm could make a significant improvement when compared with other schemes. The strategy was compared with to others strategies—Random and Fixed—which have both been largely used in the literature. The Dynamic Strategy proved to be more efficient, since it was able to serve all of the mobile user/IoTs sensors with a minimum number of UAV-BSs; thus, the developed algorithm can also be used for positioning drones to collect sensors in the IoTs, thereby enabling better coverage and signal quality from the sensors or users on the ground. In future work, an attempt will be made to determine if this solution is valid for other network scenarios and different propagation models.

Author Contributions: Software, Simulation, Methodology, Writing—review and editing, W.R.S.e.S.; Review and Editing, R.H.T. and D.L.C.; Supervision, D.L.C. All authors have read and agreed to the published version of the manuscript.

Funding: The authors would like to thank the Support Program for Qualified Production—PROPESP/UFPA (PAPQ), for supporting the research carried out in this article.

Acknowledgments: We would like to express our thanks to the Federal Institute of Education, Science and Technology of Pará (IFPA) and the Operational Research Laboratory (LPO) through the Graduate Program in Electrical Engineering (PPGEE) at the Federal University of Pará (UFPA).

Conflicts of Interest: The authors declare no conflict of interest.

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