International Journal of Computer (IJC)
ISSN 2307-4523 (Print & Online)
http://ijcjournal.org/

Mobile Network Access Points using Self Organising Drone Constellations

Isaack Adidas Kamanga[a]*, Johanson Miserigodisi Lyimo[b]

[a,b]*Assistant Lecturer Department of electronics and telecommunications engineering, Dar es Salaam Institute of Technology (DIT), 2958, Dar es Salaam, Tanzania.*
[a]*Email: isaackkamanga@gmail.com*
[b]*Email: johansonlyimo@gmail.com*

Abstract

Nowadays with artificial intelligence and automation requires much remote sensing. Sensors can be fixed or mobile. Mobile sensor networks are easy to deploy in a new location however, one of the challenges is figuring out how to interconnect these mobile sensors and link them to a core network. This paper proposes a technique of setting a mobile network that miniature base stations or access points be carried by drones in an automatically structured constellation to enable network connectivity between sensors. The paper presents a swing and adjusting technique to determine the ideal deployment of mobile base stations carried by drones, one base station per drone to connect as many sensors as possible without having prior information on sensor distribution. Swing and adjusting, coverage control, collision avoidance, and self-organizing drone constellation are all part of the algorithm. The suggested approach shows promising results according to simulations.

Keywords: Drone; Emergency communication; Mobile base station; Constellation; Deployment optimization.

1. Introduction

Remote sensing is very useful in detecting the alarming indicators of disasters like forest fire outbreak, floods, crop pests' inversion into farms, and earthquake and drainage systems overflow [15,16]. Also, we may need remote sensing in advanced agriculture crop monitoring such as monitoring pests in crops farm and capturing destructive pests and insects. In all these cases deploying a fixed terrestrial network may become economically infeasible though technically possible. According to [1] in such emergency scenarios, ground radio transmission may be obstructed, preventing emergency communications from remote sensors or people in disaster areas. According to [1] we may opt to use on-ground base stations to offer emergency communication when a disaster occurs

----

* Corresponding author.

However, this approach has one big challenge, the lack of mobility and cost issues involved in building big telecommunication towers [3, 5]. With recent developments in drone technology, we can implement the idea of [1] by deploying mobile base stations carried by these drones having a collision avoidance capability and self-organizing capability.

In this work the drone-mounted base stations are referred to as D-BSs, these D-BSs can connect cellular network users in remote areas to for instance rescue teams if an emergency communication is needed. This kind of mobile network cluster can provide a quick alternative to provide wire-free access. Also, it is possible to relocate the network to another farm in case of pests monitoring and control in advanced agriculture and hence serve us from the expenses of setting multiple fixed networks on different farms [2], [5]. For example, using a network formed by D-BSs, network users in a disaster area may be able to connect with rescue teams or other personnel in charge and get help. On the other hand, the rescue team may send important information to the victims such as asking about their locations, boosting the rescue effort. The main advantage of D-BSs is that they can be deployed in any area above the ground without being troubled by ground obstacles such as buildings and mountains and they can be relocated to another area for another emergency use or remote sensing use unlike the fixed terrestrial base stations and mobile base stations carried by vehicles which suffers a significant obstruction of the line of sight (LOS) [7].

The main challenge of D-BSs is power, however, in recent year number of researchers are been investigating the best approach of efficiently powering the drones while up there and the communication equipment they carry. A European drone company called Quaternium1 claimed to have set a record for self-powered drone endurance of four hours and forty minutes [3]. This work proposes that deploying two or more drones and ground drone bases for battery replacement, an architecture consisting of drones with switchable batteries and ground drone bases for battery replacement can achieve permanent coverage at a given site. According to [13], natural catastrophes frequently result in environmental destruction affecting the terrestrial communication lines as well as affecting people's properties as a result of this, emergent base stations must be deployed to facilitate communication between people in the disastrous area and the possible rescue personnel. In an emergency, the location of a person to be served may not be known immediately and may require prior communications between the rescue team and the person to be rescued [4,20]. The impacted areas are frequently convex due to the nature of the events. Meanwhile, a polygonal approximation can transform most non-polygon areas into polygon areas [2]. As an important assumption in this article, the sub-regions considered in the design are with no holes. This means there will be no black regions between two adjacent cells. In cellular mobile communication, cell phone with working SIM cards will continue to exchange information with their nearby base stations even if there is no communication with another handset, this is called paging. Paging help to update the location of the mobile device [4,6,7]. Another important of the D-Bs-based mobile cellular network cluster is emergency communication in periodic high dense populated regions such as in periodic religious gatherings whereby the number of fixed terrestrial base stations may not be sufficient to serve the population [6-8]. Despite these advantages, the D-Bs-based network is challenged by self-organization and power issues. This article is all about proposing an algorithm for self-organizing the D-Bs constellation.

1.1 Problem statement

At the time of the disaster, there is usually no prior information about user distribution and the number of users is normally higher compared to the servicing capability of the fixed ground network by terrestrial base stations. Therefore, there is a need of setting up a temporally drone-based network using a limited number of drones [15]. However, setting up this kind of network with a limited number of drones will be associated with one main challenge which is how do we handle the self-organizing of the moving base stations carried by the drones to serve as many users as possible from a disaster area or remote sensors.

1.2 Keywords

Unmanned aerial vehicles (UAVs), sometimes known as drones, are variously sized airplanes that lack a pilot [17]. They are employed for a variety of purposes, including photo and videography, monitoring, and base station transportation. The remote control is available for all drones. Different drones can fly at different altitudes and distances. Most amateurs utilize very close-range drones, which can often reach up to three miles. The range of close-range UAVs is about 30 miles [13]. Drones with a short range may go up to 90 miles and are mostly used for spying and intelligence gathering. Mid-range UAVs have a 400-mile operating range and can be used for meteorological research, scientific studies, and intelligence gathering. Figure 1 shows an example of a drone that can be used to carry a payload up to 5 kg thus any base station customized to this weight can be carried around comfortably by this UAV.

Figure 1: Quadcopter drone

Emergency communication is a kind of communication required during an unforeseen combination of circumstances that calls for immediate action (s). Drones are movable and controllable and thus fit well to call base stations to the area that calls for emergency communication. A mobile base station is the one that can be carried to be deployed at a new location as it depends to serve an immediate purpose whereas setting fixed base stations could be either impractical, time-consuming, or very expensive [16]. Group of these mobile base stations controlled by the same controller are termed constellations and are as per this design required to self-organize to achieve deployment optimization. Deployment optimization in this sense means to set the constellations in such a way that the utilization of radio resources in connecting customers is maximized at the area to be served without compromising other communication quality of service (QoS) parameters.

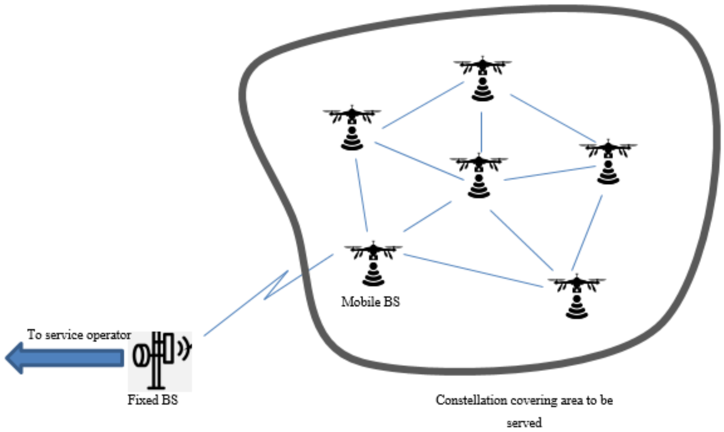

Figure 2: Constellation set up

2. Methods

This research work addresses the problem by a method here termed swing and quest. This approach involves estimating the number of base stations required for the area to be served and then randomly deploying the base stations. These base stations are mobile with the help of the moving drones in the sky. The paths of the drones are zigzag paths determined in real-time by the drones themselves [18]. The key function of the proposed algorithm is to help the drones locate the uncovered area within the boundaries of the area to be served and then cover it without colliding with the nearby drones. The important requirement for the successful swing and quest is enough to base stations pre-calculated for the area. The area is divided into polygons, the idea suggested by [7,12,17]. Each polygon is covered by one D-BS. Then the switching is done to make sure all the polygons are covered by the base stations optimally and that there are collisions among the drones. The optimization is required to cover as many cluster users as possible [6].

2.1 Access channel model

The ground base station to MS wireless channel model is modeled by the Friis transmission formula given in equation 1 in determining free space pass loss (FSPL).

$$FSPL = \left(\frac{4\pi d}{\lambda}\right)^2 \qquad (1)$$

Whereby λ is the wavelength of the radio waves while d is the distance between the base station and a mobile station (MS). For the proposed architecture, this equation needs a little adjustment. Consider the network model in Figure 3.

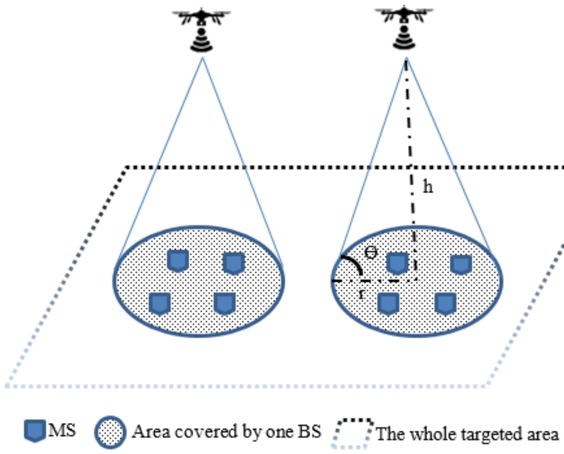

Figure 3: Mobile BSs network model

From Figure 3 the actual distance between the drone and MS (the hypotenuse of the triangle in Figure 3) is given by the Pythagoras theorem. The modified Friis transmission equation is given as Equation 2.

$$FSPL = \left(\frac{4\pi\left(\sqrt{\left(r^{2}+h^{2}\right)}\right)}{\lambda} \right)^{2} \tag{2}$$

The probability that we might have the line of sight communication between D-BS and the mobile switching center plays a significant function in deciding the path loss. To model the communication line loss, we need first to determine the probability of having an LoS connection between air and ground nodes [19]. The probability that we will have the LoS is given by Equation 3. From Equation 3 it is clear that the chance of having LoS is directly affected by the elevation angle of the drone θ positively, it increases as the angle increases.

$$\Pr obability(LoS) = \frac{1}{\left(1 + a\exp(-b(\frac{180}{\pi}\theta - a))\right)} \tag{3}$$

Whereby a and b are constant values that depend on the environmental conditions such as urban and rural areas and θ represent the angle between the vertical line from the drone to the ground which is the height of the drone above the ground. This angle can easily be computed by applying the inverse of the tan(θ), The ratio of the distance from the ground user to the point of the vertical line on the ground to the height of the drone is the tan (θ). The probability of not having the line of sight (LoS) connection between the user and D-BS is obtained by subtracting Equation 3 from 1 i.e. 1- Probability (LoS) hence as the altitude of the drone increases the chance of having LoS increases as well as the path loss.

At any point, the total path loss is the total path loss due to LoS (PLoS) and path loss due to NLoS (PLoS). If µLoS and µNLoS are the average additional loss of free space propagation which depends on the environment, c is the speed of light, f is the carrier frequency and d is the distance between the drone-BS and the MS, then the total path loss is given by Equation 4

$$PLtotal = PL(NLoS)x\Pr(NLoS) + PL(LoS)x\Pr(LoS) \quad (4)$$

Whereby $\Pr(NLoS)$ is the probability of having an online of sight transmission and $\Pr(LoS)$ is the probability of having a line of sight transmission? To determine the link budget between user and drone- BS we can rewrite Equation 4 in decibels into Equation 5

$$PLtotal\,(dB) = 20\log(\frac{4\pi fd}{c}) + \Pr(LoS)(\mu LoS - \mu NLoS) + \mu NLoS \quad (5)$$

Then if the drone-BS transmit power is Pt and the received power is Pr, the link budget is given by the difference between Equation 6 and the sensitivity of the MS. To ensure QoS the received power must be greater than the MS sensitivity which is the minimum power that can be received by the MS below which reception is impossible.

$$\Pr - Pt - PLtotal \quad (6)$$

2.2 Covering the area

Let's consider that the entire area shall be served by n drone- BSs and are randomly deployed above the ground of the area. The covered area of each drone is r shown in Figure 3. Within the circle, the probability that a user is covered is 1. The key assumptions are firstly we ignore the payload capacity of the drone-BS. The drone is equipped with GPS and can determine its location at any point, there is no drone-to-drone communication and lastly, the information about the area to be covered by the drone is known in advance such as the area coordinates. Assume that the projection position of the drone(i) is (xi, Yi), the coordinates of any point p in the ground area are (x, y), and the Euclidean distance between the drone(i) and the user p is defined as d(drone(i), p). Equation 7 is a Boolean perception model of the covered points, describing the probability that point p is covered by the drone(i).

$$C_{xy}(drone(i)) = \begin{cases} 1, d(drone(i), p) < r \\ 0, others \end{cases} \quad (7)$$

The area to be covered is calculated by Equation 8 suggested by [10], whereby Cr is the coverage ratio, NC is the number of sub-area covered and TA is the total number of sub-area in the area to be served.

$$Cr = \frac{NC}{TA} \quad (8)$$

2.2.1 Self organising algorithm

In this article, we propose that to be able to self-organize, the drones must have two kinds of sensors attached. First is the GPS to enable it to know its location and secondary the other sensor is an ultrasonic sensor in all directions to enable it to locate the nearby drone. Here it must be clear that the drone is the center of the covered footprint as shown in Figure 3. The horizontal distance between two adjacent drones is supposed to be 2r, if the distance is large than this or less than this then the algorithm tells the particular drone to swing and adjust the diameter to 2r. In theory, if the footprints are circular then we expect to have a serious problem of uncovered sub-areas, to avoid this, hexagon shapes are used which leaves no space between them. The distance from the center of one hexagon to another is still 2r as shown in Figure 4.

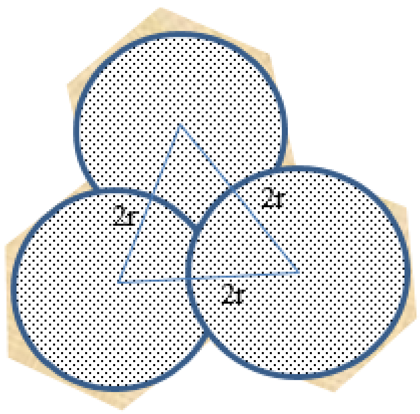

Figure 4: Overlap-free coverage mode

The next position the drone will move to is determined by three key variables namely the distance between drone and drone, the distance between uncovered area and drone, and finally the distance between drone and boundary or obstacle and the task area. The first and the last can be sensed by ultrasonic sensors. The distance between a drone and a covered area can be automatically adjusted by swinging the only assumption here is that the initial calculation done before deployment of the drones gave enough drones to cover the whole area. The proposed algorithm in this work only takes into account the two variables which are the relative distance (RD) between drone and drone and the relative distance between the drone and the boundaries or obstacles to drones.

Let the RD between drones(i) and drone (j) be dij, RD between drones(i) and area boundary is dib then the RD vector sum acting on the drone(i) is given by Equation 9.

$$d(dronei) = \sum_{j=1,\, j \neq i}^{k} dij + dib \tag{9}$$

The drone's RD dij between the drone(i) and drone(j) is decomposed into a distance vector dijx in the horizontal direction and a distance vector dijy in the vertical direction, and the RD expression between the drones is as shown in Equation 10.

$$\begin{cases} a = dijx = xi - xj \\ b = dijy = yi - yj \\ dij = \sqrt{(a^2 + b^2)} \end{cases} \quad (10)$$

So whenever the distance between adjacent drones is less than 2r or greater than 2r, the drones will move under the RD, and the updated position will be x_{new} and y_{new} given by Equation 11.

$$\begin{cases} x_{new} = x_{old} + Max\_step(\frac{dijx}{dij})\exp(\frac{-1}{dij}) \\ y_{new} = y_{old} + Max\_step(\frac{dijy}{dij})\exp(\frac{-1}{dij}) \end{cases} \quad (11)$$

Another parameter that is important to discuss is the coverage ratio. Coverage ratio can be defined as the ratio of the sum of the coverage of all D-BSs and the sum of the sub-areas (n) that D-BSs need to cover $C_{ov} = N_{cov}/ A$. Whereby C_{ov} represents the coverage ratio, N_{cov} represents the number of sub-areas that have been covered and A is the total area to be served.

2.2.2 Area decomposition and planning a path

To achieve maximum utilization of the resource, serving as many cluster users as possible while avoiding any possible collision we need a technique proposed by [3] to decompose the area to be served, we need three key steps. Firstly, we create the mathematical relation between diameter and polygon. Secondly, we need to position a drone at a minimum diameter function then from this position we find a proper direction to swing the polygon [3]. Lastly, we divide the polygon into lines that are parallel to the direction of optimum swing forming many sub-areas. The total of all sub-area gives us the total area to be served by one D-BS. Now to obtain the optimal swing direction, we apply the algorithm. The inputs to the algorithm for computation are the polygon P with an area of A polygon and the number of sub-areas. The expected result of the computation is the optimum swing direction. A polygon is divided into n sub-areas $S_1, S_2, S_3 \ldots S_n$ with each sub-area having areas $A_1, A_2, A_3, \ldots A_n$ respectively. The relationship between these variables can be summarised by Equation 12.

$$\begin{aligned} Ai &= PiA_{polygon} \\ i &= 1,2,3....n \end{aligned} \quad (12)$$

2.2.3 Drone movement control algorithm

To control where to and when to move, this study proposes three stages algorithm. The assumption is made that there exists a backhaul from the Mobile Switching Centre (MSC) to the remote area to be served and an alternative satellite connection through technologies such as VSAT can be deployed as well.

Firstly: Initialize the set-up. Each base station carried by drone is equipped with information on the task area for instance area size, and border of the area.

Secondly: Control of the movement. Each drone-BS searches for uncovered areas and obstacles and the known information. It then computes the relative distance to nearby D-BSs and their velocity. The proposal assumes that the next hope to the current BS contains all the necessary information for calculating velocity and distance. Repeat the above two stages until the stop condition is met.

Lastly: Stopping the movement: The algorithm is designed to stop the drones from moving or swinging if the area to be served is fully covered.

The detailed drone movement control algorithm is given in Figure 5.

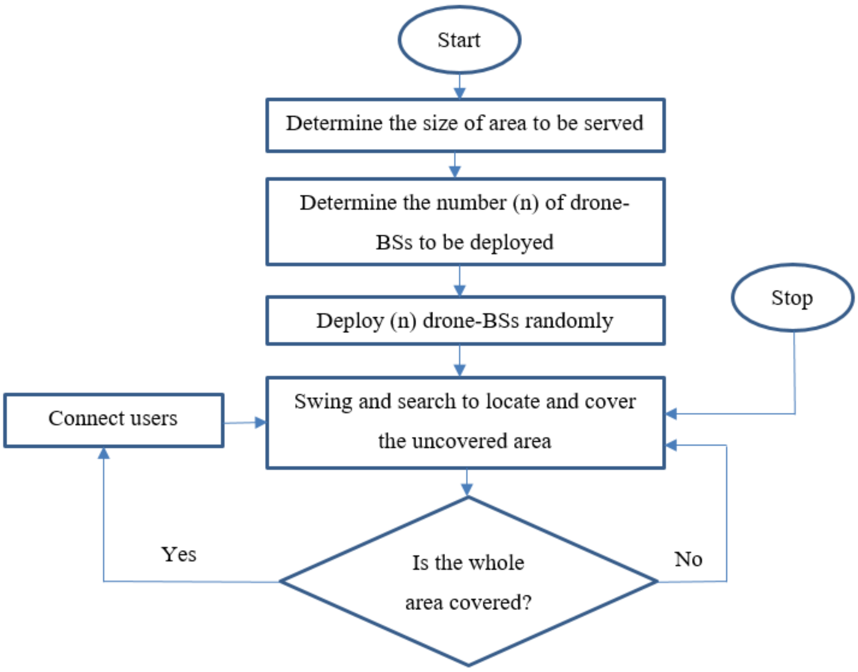

Figure 5: Movement control algorithm flow chart

3. Results and discussion

3.1 Simulation

This study used a NetSim and MATLAB combination of software to simulate the algorithm. The simulations assumed there is one ground base station linking the constellation of the moving D-BSs. Figure 6 shows the 3-D look of the single drone and its path relative to the ground base station. The simulation parameters of this study were those proposed by [12,14]. These simulation parameters are detailed in Table 1. In this study, MATLAB

2019a was used to simulate the self-organizing D-BSs network algorithm. The ten simulation parameters used are listed in Table 1. To test the universality of the algorithm, the algorithm is verified according to three different scenarios.

Figure 6: 3-D look of the single drone and its path in NetSim

Table 1: Simulation parameters

S/N	Parameter	Parameter Value
1	Covered area	1km2
2	Number of drones	10
3	Number of drones	10
4	Carrier frequency	2 GHz
5	The height of drone-BS	100 m
6	Communication distance	100 m
7	Sensing radius	100 m
8	Coverage radius	100 m
9	Maximum step size	10 m
10	Maximum iterations	100

3.2 Simulation results and discussion

To study the response of the proposed algorithm, the data shown in Table 1 were applied, and a constellation size of 10 drones was used. The total area to be served was assumed to be $1km \times 1km$ (one square kilometer) and the 10 drones were deployed randomly after pre-calculation. However, in simulation, an idea suggested by [13] was used whereby the number of drones is blindly selected in advance with the consideration that there is no fixed terrestrial base station linking the mobile cluster of base stations carried by drones. Also, to run simulations, a randomly distributed number of users had to be created, the necessary information required to create user distribution were; first, the location of the user and secondly, to generate the user distribution in the area through two-dimensional uniform random processes, an approach used by [1]. To ease the design, the provided user clusters are defined in a disk-like, having the same radius “r” as shown in Figure 3. To obtain the simulation results, the D-BSs are assumed to have no prior information on the distribution of user clusters. The results obtained are compared and the results are shown in Figure 7 whereby the number of user clusters that can be served per unit time by the proposed algorithm is higher than the results obtained from two other algorithms. The proposed algorithm's performance was compared to the results of other studies which proposed two algorithms, The attractive search and the random search algorithms [10,15,12]. In contrast to the random search method, the attraction of their own best-known position can prevent the D-BSs in the attractive search algorithm from missing the user clusters they encountered. In the random search algorithm, the drones-BSs move in random directions at first and only change directions when their coverage regions intersect the area boundaries or the coverage regions of other drones-BSs. According to [1], the relative movement of D-BSs in attractive search algorithms is led by inertia and their own best-known place where the highest number of users that can be served may be serviced. All simulations went through 100 iterations.

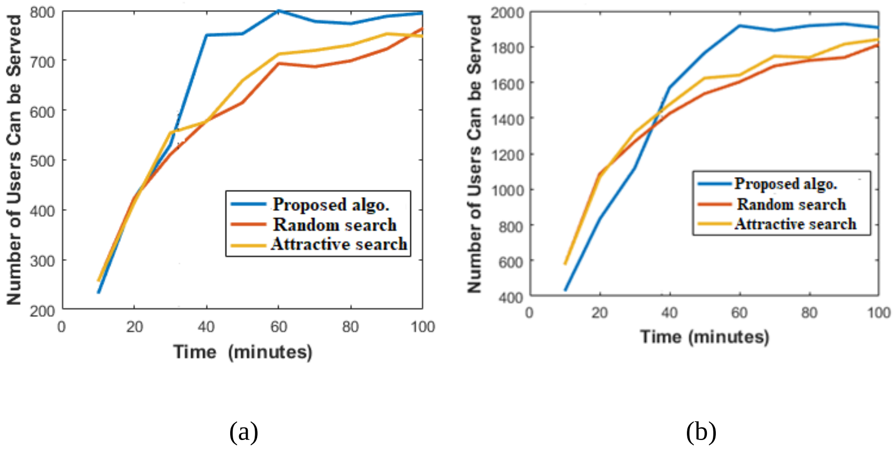

Figure 7: Comparison of results between three algorithms with 5 user clusters

The observations are depicted in Figure. Figure 7 (a) enlightens the number of connected mobile phone users if we deploy a network with 10 drones carrying base stations, the proposed algorithm can serve more users than the counterparts algorithms. On the other hand, Figure 7 (b) indicates the variations in the performance of the proposed algorithm when compared to the other two while increasing the number of user clusters to 10 (doubling the network size).

3.3 The effect of coverage radius

The variation of the coverage radius was found to have significant effects on the coverage ratio, however, it does not improve the performance of the proposed algorithm. During the simulation, the coverage radius varied from 80m, 90m, 100m, and lastly 120m. The observation can be summarised in Figure 8.

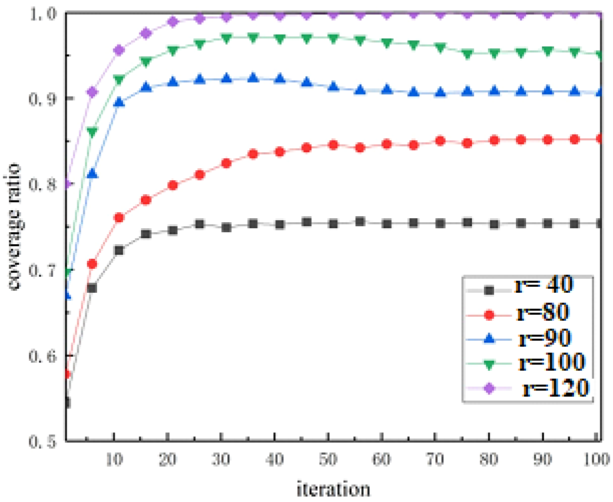

Figure 9: The effects of coverage radios on algorithm performance

4. Conclusions

The proposed algorithm showed a significant improvement over the other two compared algorithms of attractive searching and random searching. It has been found by simulation that the coverage ratio can be boosted by increasing the coverage radius. Optimization of the D-BSs-based network is a complex problem depending on the number of factors absent in the terrestrial-based network. Also, the study did not discuss the energy issues, however, energy in the drone-based network is of great concern. The research group is also engaged in energy optimization in drone-based base stations.

Acknowledgements

Researchers would like to acknowledge prof. Dening Jiang of Tianjin University of Technology and Education for his valuable review of the paper before submission for publication consideration and research results discussion. Also, researchers acknowledge Dr. Mbazigwa Mkiramweni and Dr. Joseph Matiko both of Dar es Salaam Institute of Technology for their guidance. This research was self-financed.

References

[1] Rekkas, V.P, Sotiroudis, S., Sarigiannidis, P. and Karagiannidis, G.K.; Goudos, S.K. “Unsupervised Machine Learning in 6G Networks -State-of-the-art and Future Trends,” In Proceedings of the 2021 10th International Conference on Modern Circuits and Systems Technologies (MOCAST), Thessaloniki, Greece, 5–7 July 2021; pp. 1–4.

[2] Chaschatzis, C.; Karaiskou, C.; Mouratidis, E.G.; Karagiannis, E.; Sarigiannidis, P.G. Detection and Characterization of Stressed Sweet Cherry Tissues Using Machine Learning. Drones 2022, 6, 3.

[3] Rekkas, V.P.; Sotiroudis, S.; Sarigiannidis, P.; Wan, S.; Karagiannidis, G.K.; Goudos, S.K. Machine

Learning in Beyond 5G/6G Networks—State-of-the-Art and Future Trends. Electronics 2021, 10, 2786.

[4] Fattore, U.; Liebsch, M.; Bernardos, C.J. UPFlight: An enabler for Avionic MEC in a drone-extended 5G mobile network. In Proceedings of the 2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring), Antwerp, Belgium, 25–28 May 2020; pp. 1–7.

[5] Bariah, L.; Mohjazi, L.; Muhaidat, S.; Sofotasios, P.C.; Kurt, G.K.; Yanikomeroglu, H.; Dobre, O.A. A Prospective Look: Key Enabling Technologies, Applications and Open Research Topics in 6G Networks. IEEE Access 2020, 8, 174792–174820.

[6] Selim, M.Y.; Kamal, A.E. Post-Disaster 4G/5G Network Rehabilitation Using Drones: Solving Battery and Backhaul Issues. In Proceedings of the 2018 IEEE Globecom Workshops (GC Wkshps), Abu Dhabi, United Arab Emirates, 9–13 December 2018; pp. 1–6.

[7] Livanos, G.; Ramnalis, D.; Polychronos, V.; Balomenou, P.; Sarigiannidis, P.; Kakamoukas, G.; Karamitsou, T.; Angelidis, P.; Zervakis, M. Extraction of Reflectance Maps for Smart Farming Applications Using Unmanned Aerial Vehicles. In Proceedings of the 2020 12th International Symposium on Communication Systems, Networks and Digital Signal Processing (CSNDSP), Porto, Portugal, 20–22 July 2020; pp. 1–6.

[8] Mozaffari, M.; Saad, W.; Bennis, M.; Nam, Y.H.; Debbah, M. A Tutorial on UAVs for Wireless Networks: Applications, Challenges, and Open Problems. IEEE Commun. Surv. Tutorials 2019, 21, 2334–2360. [CrossRef]

[9] Slalmi, A.; Chaibi, H.; Chehri, A.; Saadane, R.; Jeon, G. Toward 6G: Understanding network requirements and key performance indicators. Trans. Emerg. Telecommun. Technol. 2021, 32, e4201. [CrossRef]

[10] Saym, M.M.; Mahbub, M.; Ahmed, F. Coverage Maximization by Optimal Positioning and Transmission Planning for UAVAssisted Wireless Communications. In Proceedings of the 2021 International Conference on Science Contemporary Technologies (ICSCT), Dhaka, Bangladesh, 5–7 August 2021; pp. 1–4. [CrossRef]

[11] Su, Y.; LiWang, M.; Hosseinalipour, S.; Huang, L.; Dai, H. Optimal Position Planning of UAV Relays in UAV-assisted Vehicular Networks. In Proceedings of the ICC 2021—IEEE International Conference on Communications, Virtual, 14–23 June 2021; pp. 1–6

[12] Zhao, M.M.; Shi, Q.; Zhao, M.J. Efficiency Maximization for UAV-Enabled Mobile Relaying Systems With Laser Charging. IEEE Trans. Wirel. Commun. 2020, 19, 3257–3272.

[13] Pijnappel, T.R.; van den Berg, J.L.; Borst, S.C.; Litjens, R. Drone-Assisted Cellular Networks:

Optimal Positioning and Load Management. In Proceedings of the 2021 IEEE 93rd Vehicular Technology Conference (VTC2021-Spring), Helsinki, Finland, 25–28 April 2021; pp. 1–6.

[14] Kouroshnezhad, S.; Peiravi, A.; Haghighi, M.S.; Jolfaei, A. Energy-Efficient Drone Trajectory Planning for the Localization of 6G-Enabled IoT Devices. IEEE Internet Things J. 2021, 8, 5202–5210.

[15] Nikooroo, M.; Becvar, Z. Optimal Positioning of Flying Base Stations and Transmission Power Allocation in NOMA Networks. IEEE Trans. Wirel. Commun. 2021, 1.

[16] Plachy, J.; Becvar, Z.; Mach, P.; Marik, R.; Vondra, M. Joint Positioning of Flying Base Stations and Association of Users: Evolutionary-Based Approach. IEEE Access 2019, 7, 11454–11463.

[17] Lai C, Chen C and Wang L. On-demand density-aware UAV base station 3D placement for arbitrarily distributed users with guaranteed data rates. IEEE Wirel Commun Lett 2019; 8: 913–916.

[18] Haitao Z, Haijun W, Weiyu W, et al. Deployment algorithms for UAV airborne networks towards on-demand coverage. IEEE J Select Area Commun 2018; 18: 4083.

[19] Chen Y, Li N, Wang C, et al. A 3D placement of unmanned aerial vehicle base station based on multipopulation genetic algorithm for maximizing users with different QoS requirements. In: IEEE 18th international conference on communication technology (ICCT), Chongqing, China, 8–11 October 2018, pp.967–972. New York: IEEE.

[20] Alzenad M, El-Keyi A, Lagum F, et al. 3D Placement of an unmanned aerial vehicle base station (UAV-BS) for energy-efficient maximal coverage. IEEE Wirel Commun Lett 2017; 6: 434–437.