IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received April 15, 2019, accepted May 30, 2019, date of publication June 7, 2019, date of current version June 25, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2921729

Enhanced Deployment Strategy for the 5G Drone-BS Using Artificial Intelligence

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ABSTRACT The use of drones to perform various task has recently gained a lot of attention. Drones have been used by traders to deliver goods to customers, scientists, and researchers to observe and search for endangered species, and by the military during critical operations. The flexibility of drones in remote controlling makes them ideal candidates to perform critical tasks with minimum time and cost. In this paper, we use drones to setup base stations that provide 5G cellular coverage over a given area in danger. The aim of this paper is to determine the optimum number of drones and their optimum location, such that each point in the selected area is covered with the least cost while considering communication relevant parameters such as data rate, latency, and throughput. The problem is mathematically modeled by forming linear optimization equations. For fast optimized solutions, genetic algorithm (GA) and simulated annealing (SA) algorithms are provisionally employed to solve the problem, and the results are accordingly compared. Using these two meta-heuristic methods, quick and relatively inexpensive feedback can be provided to designers and service providers in 5G next generation networks.

INDEX TERMS Genetic algorithm, simulated annealing, UAV, smart city, IoT.

I. INTRODUCTION

There is a high demand for provisioning high quality of services (QoS) due to recent massive growth in everything, especially in the telecommunication sector. The rapid population growth has brought a number of challenges in telecommunications, including coverage and data traffic capacity. One promising way to mitigate some of these challenges is the utilization of intelligent systems towards smart projects such as smart cities, smart building, smart vehicles, smart grids, etc. Internet of Things (IoT) is the interconnection of these smart projects with sensing, actuation and computing capabilities via the internet. It is used to provide better services and resource management for the general population. However, the vast amount of data generated and collected requires the use of a powerful communication paradigm in order to guarantee the QoS in all these services. 3G and 4G have a few QoS advantages, such as low deployment cost, simplicity in management, extensive coverage and high security. However, they do not support Low-Cost Machine-Type Communications (MTC) with high efficiency [1]. This is an important feature for the future telecommunication because 3G and 4G have been designed mainly for optimised broadband communication [2], [3]. On the other hand, 5G is specifically designed to provide QoS to users, which means that it is capable of providing the maximum bandwidth, and reduced latency, error rate, and uptime. Additionally, 5G have increased data rate, reduced delay, as well as, enhanced cellular coverage [4]. In health care, for instance, these advantages are useful in improving the system for millions of people. Chen *et al.* [5] designed a personalised emotion-aware healthcare care system using 5G. It focuses on the emotional care, particularly for children, and mentally ill and elderly people. The proposed system uses various IoT devices to capture images and speech signals from a patient in an intelligent environment such as a smart home. This data is fed into an emotion detection module, which processes speech and image signals separately. Then it merges the obtained results to produce a final score of the emotion. The score is further analysed to determine if the patient requires attention. And if so, medics are alerted immediately. Furthermore, Poncha *et al.* [6] state that the

The associate editor coordinating the review of this manuscript and approving it for publication was Wael Guibene.

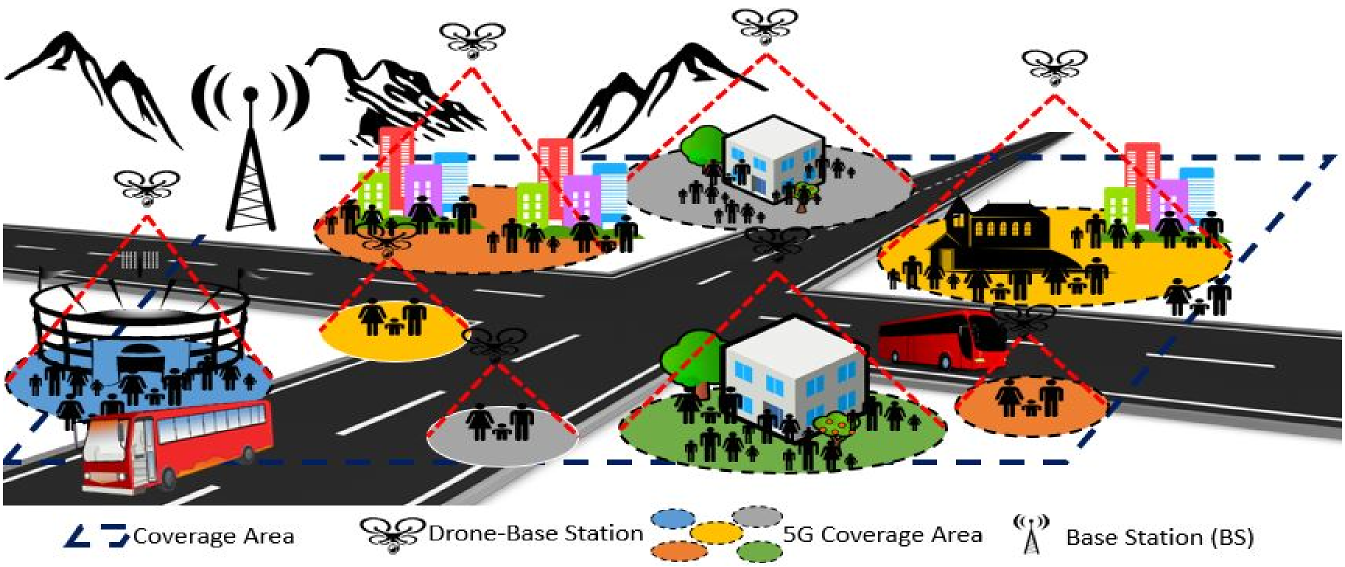

FIGURE 1. UAV-based 5G coverage in urban area.

ability of 5G to focus on heterogeneous access technology has opened a plethora of possibilities. 5G has the ability to create an interconnected world using IoT. Skouby *et al.* [7] add that such a linked system must connect smart cities, smart homes and IoT in one cohesive paradigm. 5G technology will not only offer high-speed broadband Internet connectivity, but will also support e-payments, e-transactions and other fast electronic transactions [8]. Moreover, 5G focusses on Voice over Internet Protocol (VoIP) devices. This in turn leads to high levels of data transmissions and call volumes [8].

In this paper, we work on maximizing the 5G coverage for the aforementioned applications using Unmanned Aerial Vehicles (UAVs) in urban settlements as shown in Figure 1. Wireless users expect to have unlimited and affordable internet access all the times. Increasing the number of Base Stations (BSs) in a given area is a potential way for satisfying users and providing extended 5G coverage. However, this is not an easy task. Because a few of these BSs can have light or no load at all at a particular time, while other BSs might experience very high data traffic and unnecessary overhead. The unpredictability characteristic of the user makes it hard to know exactly where and when a base station should be located. We use UAVs to counter this problem by designing drone-BSs as depicted in Figure 1. The drone-BS is flexible, and able to be placed where it is needed most, and at any particular time. And hence, it efficiently provides 5G coverage for the users at all times. Kalantari *et al.* [9] state that drone-BS can be used to provide assistance to the ground BSs with high data rates as well when additional space and time is required. There is a growing number of research work being done on drone-BS in cellular networks. However, one critical challenge that has not been given much attention is finding the lowest number of drone-BS and their respective positions in a given 3D space, required to provide maximum 5G coverage with guaranteed QoS. The main contribution of this paper is therefore to model this challenge into a linear optimization problem, and use Simulated Annealing (SA) and Genetic Algorithm (GA) metaheuristic algorithms to solve it. GA and SA algorithms have been chosen due to their ability in providing fast and efficient solutions to service providers. These two algorithms are applied in a system of UAVs communicating in a multi-hop fashion. This system helps in reducing the amount of energy consumed by the Drone-BS since we do not require wide-range transmitters, which are high power consumers. The two algorithms are used in extensive simulations, where coverage graphs are drawn and numerical results are compared in order to determine which algorithm can provide quick and more accurate solutions.

The rest of the paper is organized as follows. Section 2 talks about some of the works that have been done relating to this study. Section 3 discusses some of the main challenges faced by aerial sensor networks while Section 4 presents the model of the system. Section 5 discusses the findings of this study. Finally, Section 6 presents our conclusions and future work. In order to further assist the reader, a list of used abbreviations in this article and their definitions are presented in Tables 1 and 2.

II. RELATED WORK

The efficiency of optimal drone positioning has attracted a lot of interest among researchers and academicians. Zorbas *et al.* [10] introduces a minimum cost drone location problem. In their work, Zorbas *et al.* use a two dimensional terrain to find the optimal location and number of drones/UAVs to observe given targets, which could be mobile or static in a given area, the authors develop linear and non-linear optimization equation by considering the coverage of the drones and the energy consumed.

TABLE 1. Abbreviations and definitions.

Abbreviation	Description
SA	Simulated Annealing
GA	Genetic Algorithm
UAV	Unmanned Aerial Vehicle
WSN	Wireless Sensor Networks
MWSN	Multimedia Wireless Sensor Network
MGSAA	Modified Genetic and Simulated Annealing Algorithm
BS	Base Station
ILP	Integer Linear Program
MDLP	Mobile Drone Location Problems
PM	Probability of Mutation
PC	Probability of Crossover
SDLP	Static Drone Location Problems
5G	5^{th} Generation of cellular networks
BS	Base Station
Drone-BS	Drone Base Station

TABLE 2. Notations and descriptions used in this study.

Notation	Description
T_0	Initial temperature
δ_0	Initial solution
α	Cooling factor
m	Number of stages
n	Number of moves
δ_F	Final solution
δ	Current solution
δ_{Temp}	Temporary solution
σ	move operator
f	Fitness function
T_t	Temperature at time t
PM	Probability of Mutation
PC	Probability of Crossover
G_{max}	maximum generation number
PS	Population size
BFS	Best fitness solution

Moreover, Tuba *et al.* [12] present a study in which they look into a recent brainstorm optimization algorithm. It aims at finding the optimal positions for static drones in a monitored area such that their coverage is maximized. The algorithm was used to solve the placement problem for both uniformly and clustered targets. Obtained results showed that the proposed algorithm is very efficient for solving drone placement problems. In [10]–[12], authors try to find the optimal drone locations for observational and monitoring purposes only. Unlike our work, in which we target a new trend in the 5G coverage.

Furthermore, we can consider UAVs as aerial wireless base stations when cellular networks are out of service [13]. This system can be used when disasters such as flood and earthquake affect the existing communication system. Shakhatreh *et al.* [14] talk about finding an optimal position for the UAVs such that the sum of time durations of uplink transmissions is maximized. They use a gradient projection-based algorithm to find the optimal placement of a single drone-BS by considering the uplink scenario as a constraint. Authors prove their hypothesis by presenting detailed simulation results for the optimization problem under different cases.

Kalantari *et al.* [9] present a study on the number of 3D placement of drone base stations. In this study, the authors use a heuristic algorithm to optimally place drone base station in a region with different target densities. The goal of the study is to find the minimum number of drones and their 3D placement such that all users are served. The simulation results obtained from the study showed that the proposed system can yield QoS constraint of the network. Unlike the attempts in [11]–[14], our work considers time-efficient solutions. We use heuristic GA and SA to find the optimal drone locations for 5G coverage, while considering energy and cost constraints.

Numerous works have been done to compare the different results obtained by different heuristic optimization algorithms. In [15], Rodriguez *et al.* compare four studies that have been done on routing and wavelength assignment with the aim of supporting and improving traffic related problems. Moreover, the authors perform various simulations using the optimizing algorithms, Simulated Annealing (SA) and Genetic Algorithm (GA). The results obtained revealed that the optimizing algorithm produced better results compared to the other algorithms.

Yu *et al.* [16] propose a new heuristic algorithm used to test generation of data during software testing process. Modified Genetic and Simulated Annealing Algorithm (MGSAA) was used to perform different experiments. Yu et al presents the simulation results and conclude that the proposed method generates high quality results compared to Genetic Algorithm (GA). In [17], Thompson *et al.* used GA and SA metaheuristic algorithms to optimise a topological design network and compare the results. The authors concluded that the average GA solution costs less than the average SA solution.

However, Thompson *et al.* [17] and other overviewed studies in this section compared the cost of GA and SA algorithms to determine the optimal solution for a topological network design. In our work, we use GA and SA to determine the optimal position for 5G drone base stations given the constraints of coverage, energy and cost. Hence, we aim at improving parameters such as the data rate, latency and throughput.

III. CHALLENGES IN UAVs NETWORKS

Drone base-stations have been proven to be a good candidate in providing high-throughput in wireless communications for situations requiring moderately stable links and network topologies. This is due to their unique ability in hovering/moving with the target at close distances. However, there are few challenges that need to be addressed when it comes to aerial sensor deployment. Aerial sensor network face numerous challenges, especially in the monitoring of outdoor critical situations where the severity of the environment such as high temperatures, heavy rains, storms and the likes, destroy the installed aerial sensors [18].

In this work, flying drones are not only used as aerial sensors, but also as access points (BSs). Consequently, new challenges are expected to rise in comparison to conventional sensor networks. Resource allocation is one of the most important aspects. Sample limited resources for sensor nodes include power, memory and communication bandwidth. Usually sensor nodes consume little power while performing some activities such as sensing, data storage and simple data aggregation. However, there are other operations, which consume a significant amount of power such as the image analysis in multimedia and cellular applications. Hence, further research should be focused on determining the trade-offs between locally storing, communicating and processing data, and consequently develop energy-efficient sensory paradigms.

In aerial sensing platform, most of the power is consumed during UAV propulsion, power consumed during sensing, processing, and communication is usually relatively negligible, and hence can be ignored [19]. Therefore, for efficient power consumption, one has to plan the flight path of the UAV. For instance, ascending consumes more power than flying at a constant altitude [10]. Moreover, weather conditions can have a significant effect on the UAV's power consumption. Sensors on the UAV can be used to send back information about direction and speed of the wind during the flight for instance, and adapt accordingly.

Moreover, aerial WSN communication is different in comparison to other communication networks. When UAVs are flying, they need to exchange data (current position, speed, direction, etc.) with each other as observed from Figure 2. Individual UAVs need to exchange their information after only a few seconds. However, multiple UAVs flying simultaneously need to know and transmit their position more accurately. Hence, UAVs' position data is exchanged every few milliseconds. This necessitates a link with low latency and a wide communication range.

In [20], Asadpour *et al.* acknowledge the importance of aerial sensor networks. A few challenges/issues incurred in this paradigm have been addressed, in addition to discussing a few possible solutions, as well. It has been reported that mobility and heterogeneity of the utilized nodes (or BSs), can cause connectivity problems because of their severe influence on the distance between the intra-communicating nodes. This can significantly change the flying network topology. And hence, effective routing, scheduling, and data forwarding techniques must be further investigated in this area. Mitchell *et al.* [24] proposed a scheduling algorithm, which can be applied in such dynamic topologies. Their algorithm computes the shortest path to the sink node dynamically, and

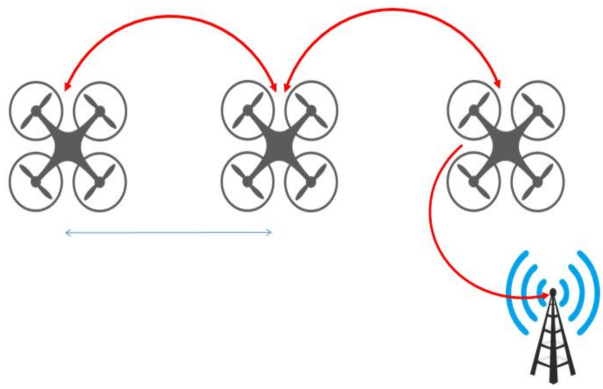

FIGURE 2. UAV communication with each other and BS.

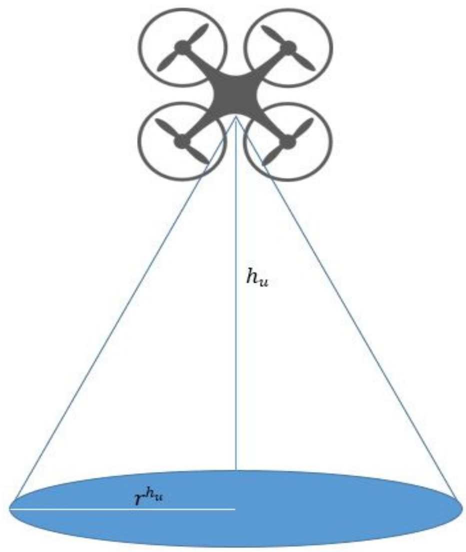

FIGURE 3. UAV cellular cover.

hence, it reduces latency. This approach can also be applied in this study.

IV. SYSTEM MODELS

In this work, the considered system consists of a common sink (BS), to which information is sent and dispatched. Since a UAV might be out of the communication range of the BS, the UAV can send/relay its data to the nearest UAV. The latest can in turn forward the information to the next available one until it reaches an UAV in the communication range with the BS [18]. Figure 2 below demonstrates the network architecture of the considered UAVs system. In Table 2, a summary of the assumed/used notations in this paradigm is provided.

In order to obtain an optimal number of drones to be used in maximizing the 5G coverage, it is imperative that drones are located in the correct position. This is of utmost importance so that it obtains the maximum coverage while minimizing the number of UAVs. This in turn can reduce the cost. Younis *et al.* [21] claims that sensor placement is a challenge by itself. Considering the limited sensing and communication sensor range, as well as the restricted resources such as energy

FIGURE 4. Virtual coordinates inside coverage area.

and coverage, make it more complicated problem. In their study, Quaritsch *et al.* [19] investigate the use of UAVs in disaster management. They discuss the challenges facing the networked UAVs as well as focusing on their optimal placement. In doing so, Quaritsch *et al.* mathematically formulated the coverage problem and presented potential assessment results. Authors took into account two optimization criteria, the first one is the quality of the image taken, which refers to the coverage quality of the UAV. The second one is the consumption of resources, which involves the communication bandwidth and the energy used in flying. The observation area and the forbidden area are drawn by the user using worldwide coordinates, namely the longitude and latitude. However, as described by Quaritsch et al, the entire process of optimizing sensor placement is done using relative coordinates. Therefore, the first step is to transform the worldwide coordinates into the relative coordinates by selecting an arbitrary origin inside the observed region. Hence formulating the x- and y- axis to go eastwards and northwards respectively, as shown in Figure 4.

Zorbas *et al.* [10] present a study that determines the optimal static and dynamic drone positioning in a selected area, to minimize cost and maximize coverage. It was shown that drones must have a maximum and a minimum observation altitude. That is because the height of the UAV is directly proportional to the coverage area it can observe. However, the higher the UAV is, the more energy it consumes. Therefore, there must be a threshold on the maximum height/altitude an UAV can be placed at. Park *et al.* [11] propose a coverage decision algorithm, which aims at solving handover problems caused by time-varying aerial environments. The algorithm takes into account the height of the drone needed to provide a better coverage. According to [11], controlling the height of the drone helps to provide better drone coverage.

The relationship between the targeted area coverage and the height of the drone was formulated by $A = \pi\left(R^2 - h^2\right)$, where A is the coverage area of the drone, h is the drone's height, and R represents the radius of the drone's wireless transmitter. Obviously, this area A is equal to πR^2 when the height h is equal to 0. The main focus in [10] and [11], was to minimize the cost, and hence, the number of drones and energy consumed. Accordingly, our assumed UAVs can fly to a maximum height equal to h_{max}, and a minimum height equal to h_{min}, that maintain a specific coverage radius r^{h_u} [10]. Figure 4 shows a rectangle with length x_{max} and width y_{max}, which represent the area of interest. Therefore, targets could be in any arbitrary location in an area of $x_{max} * y_{max}$. We assume that there is a position (x, y, h) that a drone can be located at instantaneously. Let **U** denote a set of available drones, and **T** is the set of targets.

Each target $t_i \in \mathbf{T}$ has position $\left(X_{t_i}, Y_{t_i}\right)$. Drone $u \in \mathbf{U}$ has position (X_u, Y_u, h_u). For h = 0, the distance between the target and the drone is:

$$D_{t_i}^{u_x,u_y} = \sqrt{\left(X_{t_i} - X_u\right)^2 + \left(Y_{t_i} - Y_u\right)^2} \tag{1}$$

Each drone u, has a communication range θ in form of a disc in area $x_{max} * y_{max}$ as shown by the blue area in Figure 3. And it has a radius of r^{h_u}, which depends on the height of the drone h_u. The larger the value of h_u, the longer radius r^{h_u} we have. There are two important decisions that must be made at this point, the first one is to determine the position (X_u, Y_u, h_u) of the drone $u \in U$ (coordinates) and the second one is to find the target $t_i \in T$ in the area of interest.

For the first problem (Position of drone):

$$\delta_{xyh}^{u} = \begin{cases} 1, & \textit{if the drone u is located at } (x, y, h) \\ 0, & \textit{other wise} \end{cases} \tag{2}$$

And for the second problem (Target observed):

$$\gamma_{t_i}^{u} = \begin{cases} 1, & \textit{if the target } t_i \textit{ is in the range of drone u} \\ 0, & \textit{other wise} \end{cases} \tag{3}$$

The objective is to cover all the targets using at least one drone. Each drone consumes a total energy E formulated as:

$$E = (\beta + \alpha h)\, t + P_{max}\,(h/s)\,, \tag{4}$$

where β is the minimum power needed to hover at almost zero altitude, α is the motor speed multiplier, P_{max} is the maximum motor power, and s and t are speed and operating time, respectively. Also, h represents the drone's height. The term $P_{max}\,(h/s)$ is used to show the power used to rise the drone to a height h at speed s. It is worth pointing out here that β and α depend on the weight of the drone and the used motor characteristics. Therefore, we can formulate our placement problem as follows.

$$\begin{aligned} &\text{Minimize} f\ (\delta) \\ &\text{Subject to ,} \\ &\qquad \sum_{(x,y,h)} \delta_{xyh}^{u} \leq 1 \textit{ and } D_{u'}^{u_x,u_y} \leq r^{h_u} \quad \forall u, u' \in \boldsymbol{U} \end{aligned} \tag{5}$$

Knowing that each drone u can be located in at most one position that is with the communication range of at least one neighbouring drone. Where $D^{u_x,u_y}_{u'}$ is the Euclidian distance to the nearest neighbouring drone u'.

$$\gamma^u_{t_i} \le \sum_{(x,y,h)} \delta^u_{xyh} \left(\frac{r^{h_u}}{D^{u_x,u_y}_{t_i}}\right) \quad \forall u \in \boldsymbol{U}, t_i \in \boldsymbol{T} \tag{6}$$

With the above constrain, we set the value for $\gamma^u_{t_i}$. If $r^{h_u}(radious\_range)$ is less than $D^{u_x,u_y}_{t_i}(distance)$, then $\gamma^u_{t_i}$ is equal to 0. In other words, if the target is outside the communication range of the 5G transmitter mounted on the drone, then the target cannot use that drone to access 5G. Therefore, the variable $\gamma^u_{t_i}$, can get either the value 0 or 1.

$$\sum_{u \in \mathbf{U}} \gamma^u_{t_i} \ge 1 \; t_i \in \mathbf{T} \tag{7}$$

The above constrain ensures there exists at least one drone observing each target. The following equations show the solution space of the aforementioned $\gamma^u_{t_i}$ and δ^u_{xyh} decision variables.

$$\delta^u_{xyh} = \{0, \;\; 1\}, \quad \forall (x, y, h), 1 \le x \le x_{max} \tag{8}$$

$$1 \le y \le y_{max},$$

$$h_{min} \le h \le h_{max}, \quad u \in \boldsymbol{U} \tag{9}$$

$$\gamma^u_{t_i} = \{0, \;\; 1\}, \quad \forall t_i \in \boldsymbol{T}, u \in \boldsymbol{U} \tag{10}$$

And hence, $f(\delta)$, to be minimized, can be formulated as follows:

$$f(\delta) = A - \sum_{u \in \mathbf{U}} \delta^u_{xyh} * A'_i \tag{11}$$

where A is the total area to be covered, and A'_i is the area covered by the ith UAV. By integrating Eqs. (11) and (4), to minimize the total energy consumed, while considering the movement time of the drone, $f(\delta)$ becomes:

$$f(\delta) = \beta \sum\nolimits_{(x,y,h)} \sum\nolimits_{u \in U} \delta^u_{xyh} t + \alpha \sum\nolimits_{(x,y,h)} \sum\nolimits_{u \in U} h\delta^u_{xyh} t + \frac{p_{\max}}{s} \sum\nolimits_{(x,y,h)} \sum\nolimits_{u \in \boldsymbol{U}} h\delta^u_{xyh} \tag{12}$$

We propose two alternatives to solve the placement problem. Genetic algorithm and Simulated Annealing would be used to calculate the number of drones and their respective position in a given area while maintaining coverage and lifetime constrains in the 3D deployment area.

Algorithm 1 Simulated Annealing Pseudo code

1. Initialize: T_0, δ_0, α,m, n
2. $\delta = X_0$, $\delta_F = X_0$, $T_1 = T_0$
3. **For i=1 to m**
4.   **For j=1 to n**
5. $\delta_{Temp} = \sigma(\delta)$
6.   **If**: $f(\delta_{Temp}) \le f(\delta)$ then
7. $\delta = \delta_{Temp}$
8.   **End If**
9.   **Else if**: $U(0, 1) \le e^{-\left(\frac{f(\delta_{Temp}) - f(\delta)}{T_t}\right)}$ then
10. $\delta = \delta_{Temp}$
11.   **End Else if**
12.   **If:** $f(\delta) \le f(\delta_F)$ then
13. $\delta_F = \delta$
14.   **End If**
15.   **End For**
16. $T_{t+1} = \alpha.T_t$
17. **End For**
18. **Return** δ_F

Algorithm 2 Genetic Algorithm Pseudo code

1. Initialize: PS, G_{max}, PC, PM
2. $\delta = (\delta^u_{xyh})^+$: Generate initial random solutions
3. $f(\delta)$: Calculate fitness for random solutions
4. Select BFS
5. **For** g = 1 to G_{max}
6.   **For** i = 1 to PS/2
7.   Select two parents
8.   Crossover with PC
9.   Mutate with PM
10.   **End For**
11.   Replace parents with children
12.   Update BFS
13. **End For**
14. **Return** BFS

In Algorithm 1, we used SA to find the minimum number of drones such that line 1 is initializing the aforementioned placement problem parameters. T_0 is the selected initial temperature of the system. We use this parameter to enable us to accept or reject certain drone placement solutions. The higher the value of T_0, the higher the probability of accepting a bad solution. Hence, we start by allocating a maximum temperature to T_0. We gradually reduce the temperature of the system using the cooling factor α, which was selected in this work as 0.95. As the temperature reduces, so does the probability of accepting bad solutions. In line 1, we also initialize the initial solution δ_0, which is heuristically selected for better results. Moreover, m is representing the number of stages and n is the count of moves per stage with a certain temperature in SA algorithm. The number of moves allows us to explore the neighbourhood for possible solutions (i.e., UAVs' locations). Therefore, it is important that this value is carefully chosen. Line 2 assigns the initial solution to δ and to the final solution δ_F. It assigns also the initial temperature to the current temperature T_1. Line 3 – 17 iterates over the initialized number of stages, where we decrement the temperature value after every stage. Lines 4 – 15 iterates over the number of moves at a given stage, where we get to explore the neighbouring solutions under a constant temperature. In line 5, we find a neighbouring solution using the move operator $\sigma(\delta)$, where $\sigma(\delta) = \delta + N(0, 1)$. We assign this solution to a temporary solution δ_{Temp}. Line 6 checks if the temporary drone placement solution is better than the current one. To achieve this, we substitute both the temporary and the current solution to the fitness function shown in Eq. (11). Line 7 assigns the temporary solution to the current solution, if the condition in line 6 is satisfied. Line 8 ends the "If" statement. Line 9 to 11 covers an "Else if" statement. Line 9 uses the current temperature T_t, which represents the temporary solution and the current solution, to find an exponential value. The value is compared with a random number (between 0 and 1 exclusive) to determine whether the temporary bad solution shall be accepted or not. Line 10 assigns the temporary solution to the current solution, if the condition in line 9 is true. Line 11 ends the "Else if" statement. Line 12 – 14 represents another "If" statement. Line 12 checks if the current drone placement solution is better than the final solution using the fitness function. Line 13 assigns the current solution to the final one, if the condition in line 12 is true. Line 14 ends the "If" statement while line 15 ends the second "for" loop. Line 16 computes the next stage temperature of the system T_{t+1} using the cooling factor. Line 17 ends the first "for" loop and finally line 18 returns the selected final solution δ_F after all iterations have been completed. In Algorithm 2, we apply GA on the same problem to find the minimum number of drones and their optimal positions for the maximum coverage. We begin by initializing the aforementioned parameters in line 1. PS is the population size, which represents the count of the initial solutions to be selected. G_{max} is the maximum generation number for which an optimal solution is obtained. PC and PM are the probability of crossover and probability of mutation, respectively. These parameters are selected in order to evolve from one generation to the next. In line 2, we generate the initial solution in accordance with PS. This solution is represented by the set of 0's and 1's. In line 3, we compute the fitness of all initial solutions. And in line 4, we select the solution with the best fitness value. Lines 5 – 10 iterate over a specific generation number, while line 6 – 13 iterates for number of times equal to half of the population size. We iterate over half the population size because at every generation we select two parents for the crossover operation. In line 7, we select two parents. Then, in line 8, we produce two children by applying the crossover operation. In line 9, we mutate the produced children using a probability equal to PM. In this case, we consider each element in each solution. In line 10, we end the second "for" loop. In line 11, we replace all the parents with the newly produced children, forming the next generation of the evolved drone placement solutions. In line 12, we update the best-found solution (BFS) by substituting the newly produced solutions in the fitness function (i.e., Eq. (11)) so that we can find the best solution. This solution is compared with the previous BFS. If it is better, we update the BFS. In line 13, we end the first "for" loop, and in line 14, we return the BFS.

V. RESULTS & DISCUSSIONS

In this section, an in-depth analysis of the simulated results is presented. Java and Python were used to execute SA and GA respectively. An area of 80 kilometres squared was selected to be observed, with each drone having a 5G transmitter with an average range equal to 10 kilometres squared. For Simulated Annealing, initialization was done as follows, an initial

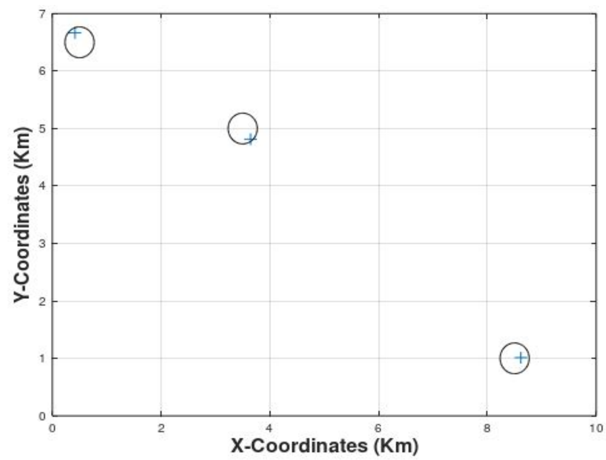

FIGURE 5. Three targets to cover.

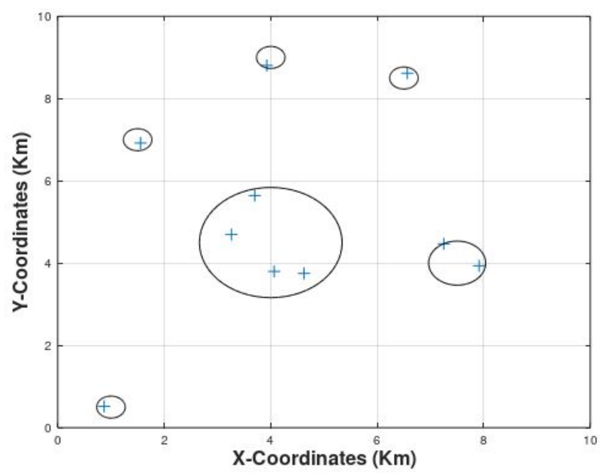

FIGURE 6. Ten targets to cover.

temperature of 300 was chosen, and an initial solution in terms 0s and 1s was chosen (1 indicating the presence of a drone in that vertex, 0 indicating its absence). The movement operator (α) in SA was set to be equal to 0.95, while m and n were set as 500 and 200 respectively. Additionally, initialization for genetic algorithm was done as follows: a population size of 8 was selected, stopping criteria (i.e. G_{max}) as 50, PC (Probability of Crossover) of 0.5 and PM (Probability of Mutation) was chosen as 1.

In Figures 5 – 7, we observe the number of drones required for a randomly generated count of targets on the ground. Figure 5 shows three targets that need to be observed. We notice that these targets have been located far away from each other. Therefore, one drone is not enough to cover all of them and three drones have been used in order to cover all targets. In Figures 6 and 7, we increase the randomly distributed number of targets to be equal to 10 and 22, respectively. We notice that the optimal number of drones required for this configuration increases to six in both figures. Accordingly, we remark that if the number of targets is equal to x, then the required number of drones to cover all targets

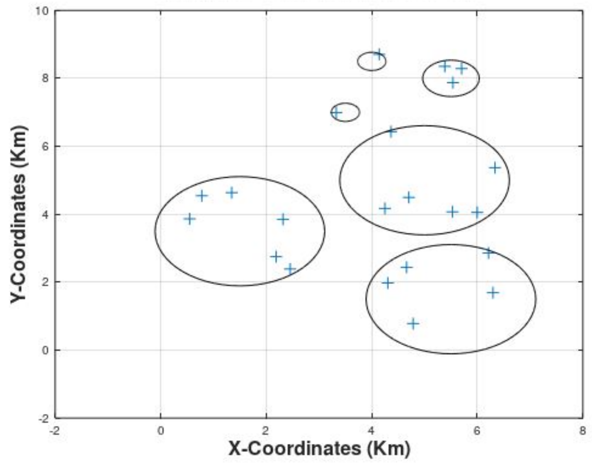

FIGURE 7. 22 targets to cover.

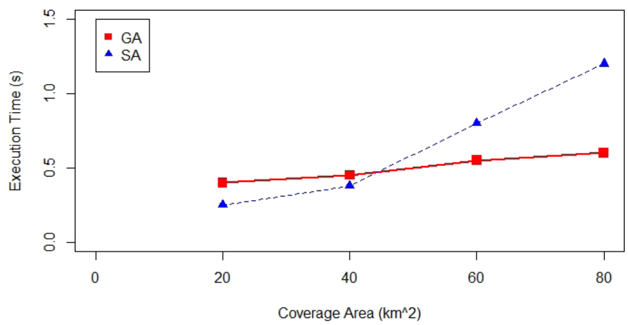

FIGURE 8. Execution time vs coverage area.

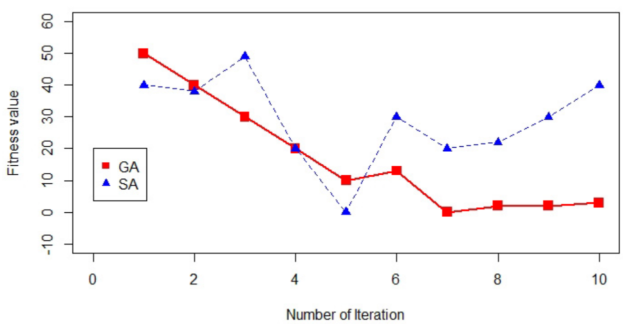

FIGURE 9. Fitness function behaviour.

can range from 1 to x. For example, if two targets are out of the communication range of a single drone, then we need two drones. However, if the two targets are within the communication range of a single drone, then we only need one drone. Therefore, we conclude that the configuration (distribution) of the targets in the covered area has a key influence on the minimum number of drones required to cover these targets.

Figures 8 and 9 below show the average execution time/fitness value over 100 runs for both SA and GA. The relative precision stopping criterion is used. Simulation runs are stopped at the first checkpoint when the condition

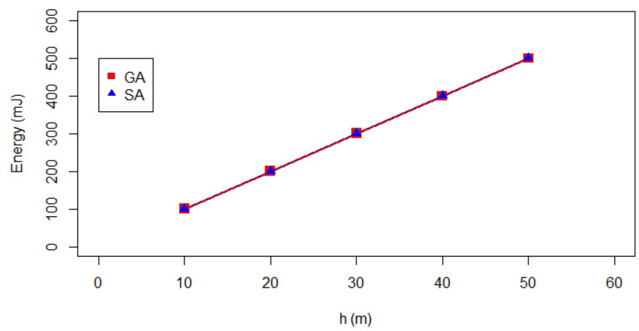

FIGURE 10. Energy consumed vs. the average height (h) of the UAVs.

$\delta \leq \delta_{\max}$ is met. Where $\delta_{\max}$, which can have a value between 0 and 1, is the maximum acceptable value of the relative precision for confidence intervals at the $100(1-\alpha)\%$ significance level. All obtained results from the simulations are within the confidence interval of 5 % with a confidence level of 95%. And thus, both default values for α and δ are set to 0.05. This can help in assessing the evolutionary convergence for algorithms. Figure 8 below shows the execution time for both SA and GA with a varied coverage area. In this setup, the area covered by each drone is held constant, while the total area of interest is increased from 20 to 80 kilometres square. We can observe that the execution time for both algorithms lie between approximately 0.29 seconds and 1.2 seconds, with SA recording the fastest and GA recording the slowest time. From the obtained graph we also see that SA records the fastest time until the total area of interest is equal to 44 kilometres square, where both algorithms have the same execution time. However, when we increase the coverage area further, the execution time for SA slows drastically, while that of GA also slows but not as fast as that of SA. Consequently, GA realizes a faster execution time than SA for a coverage area greater than 44 kilometres square.

Therefore, we can clearly state that SA is capable of generating relevant solutions faster than GA when the coverage area is small. However, for larger areas to be covered by the UAVs, it is efficient to use GA as its time to generate optimal solutions is much shorter than SA.

In Figure 9, we analyse how both algorithms produce optimal solutions by tracking the fitness functions against the number of iterations. From the figure, we observe that genetic algorithm consistently produces a better fitness function output than the previous one until we get to the fifth iteration, where we see a slight deterioration. However, the general form of the GA function depicts that the parent selection and replacement method used in our algorithm, produced optimal solutions in each iteration. On the other hand, we observe that SA is more unpredictable in comparison to GA. This instability can be attributed to the nature of SA algorithm in finding the optimal value. That is why SA requires more computation power in comparison to GA as reported in [25]. Where the major drawback of SA is its slow convergence towards an optimal value [26]. This appears clearly in Figure 9, where

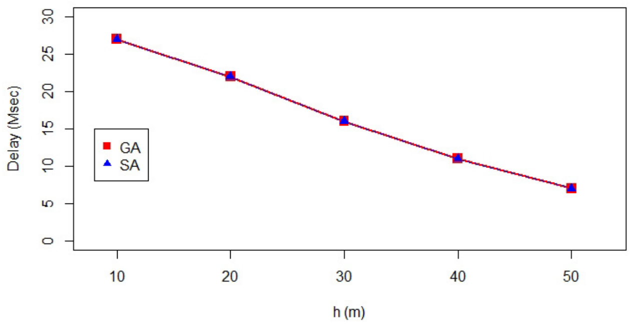

FIGURE 11. Average delay vs. the average height (h) of the UAVs.

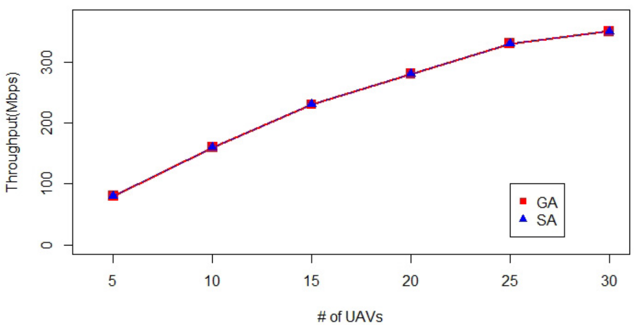

FIGURE 12. Throughput vs. the count of used UAVs.

SA algorithm experiences more local optimal values than GA. Hence, it is more likely to get stuck on a local optimal value in SA than in GA. The figure, therefore, suggests that we have better chances in reaching the global optimal value, when GA is applied rather than SA.

In Figures 10 – 12, we examined more communication-relevant parameters such as the average packet delay, energy consumption, and network throughput, while varying the average height and count of the utilized UAVs in the network. We applied this experimental work on the optimal solutions found by GA and SA. Since both algorithms were able to find the same optimal solution, both of them, GA and SA, have experienced identical behaviour.

In Figure 10, the average energy consumed versus the height of the positioned UAVs has been reported. Obviously, there is a linear relationship between the average consumed energy per delivered data packet and the height of the UAVs. This can be returned to the proportional relationship between the distance and the required transmission power [27].

In Figure 11, we testify the average experienced delay per packet while varying the average height of the UAV. In line with the aforementioned height discussions, when we increase the UAVs height values from 10 – 50m, the delay is decreasing monotonically. This is because of the coverage increment in the 3D space that allows lower number hops between the source user equipment (target) and the final destination (BS).

We examined also another critical communication metric in Figure 12, which is the overall network throughput measured in Megabytes per second (Mbps). This metric represents the amount of useful work a number of connected/networked UAVs can perform per the time unit in terms of the total data bytes that have been successfully delivered at the BS. We notice that as the number of used UAVs increases, the network throughput increases, as well. This makes sense because the more UAVs we have, the more alternative routes towards the BS will evolve also. This leads to better data delivery chances. However, this increment in terms of throughput reaches to a saturation level after a specific number of UAVs, where it stays in a steady state no matter how much extra UAVs are added.

VI. CONCLUSIONS

In this paper, we propose a framework for the optimal number of drone-BS and their positions determination. This framework is needed to provide the 5G cellular coverage to a given region, while considering the 5G transmitter's coverage range and energy constrains of the drones. The framework is very useful in providing coverage for outdoor critical events such as hurricane disasters, fire accidents, and densely populated areas such as urban areas and stadiums. We used two meta-heuristic algorithms, SA and GA written in two different languages, to find an optimised solution. The results from both algorithms were obtained, graphed, and analysed. The results obtained in this study show that SA takes precedence when the coverage area is small. However, for the extended coverage area, faster results are obtained using GA rather than SA. Moreover, our simulation results show that it is commonly possible to settle on a local optimal value when SA is applied, which is not the case with GA. Generally, we conclude that using GA can provide better results in timely manner for outdoor UAV critical applications. In the future work of this study, we would like to analyse the optimal deployment problem in indoor environments, while assuming dynamic UAVs.

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