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Wireless Coverage for Mobile Users in Dynamic Environments Using UAV

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ABSTRACT In this paper, the dynamic deployment of a single UAV as an aerial base station in providing wireless coverage for mobile outdoor and indoor users is studied. The problem of finding the efficient UAV trajectory is formulated with the objective to minimize the required UAV transmit power that satisfies the users' minimum data rate. The proposed solution to the problem considers the users' movement in a search and rescue (SAR) operation. More specifically, the outdoor rescue team members are considered to move in a group with the reference point group mobility (RPGM) model. Whilst, the indoor rescue team members are considered to move individually and in a group with random waypoint and RPGM models, respectively. The efficient UAV trajectory is developed using two approaches, namely, heuristic and optimal approaches. The employment of the heuristic approach, namely particle swarm optimization (PSO) and genetics algorithm (GA), to find the efficient UAV trajectory reduced the execution time by a factor of $\simeq 1/60$ and $\simeq 1/9$ compared to that when using the optimal approach of brute-force search space algorithm. Furthermore, the use of PSO algorithm reduced the execution time by a factor of $\simeq 1/7$ compared to that when the GA algorithm is invoked.The performance of the dynamic UAV deployment also outperformed the static UAV deployment in terms of the required transmit power. More specifically, the dynamic UAV deployment required less total transmit power by a factor of about $1/2$ compared to the static UAV deployment, in providing wireless coverage for rescue team to perform SAR operation within a rectangular sub-region.

INDEX TERMS Genetic algorithm, particle swarm optimization, random waypoint, reference point group mobility model, unmanned aerial vehicles.

I. INTRODUCTION

Recently, Unmanned Aerial Vehicles (UAVs) have been used in many civilian applications, such as real-time monitoring, infrastructure inspection, remote sensing, search and rescue operations, delivery of goods, surveillance, precision agriculture, and to assist in providing wireless coverage [1].

UAV can be used as an aerial base station as a supplement to the existing terrestrial base station when the wireless network is overloaded during a massively crowded special event, or to provide reliable communications for ground users when the infrastructure of the terrestrial base stations are damaged due to natural disasters, such as tsunami, floods and earthquake [1], [2]. Furthermore, the deployment of UAV as an aerial base station that operates at an altitude that is referred to as low altitude platform (LAP), provides higher chances of line-of-sight (LOS). Whilst, its ability to adjust the altitude and mobility enables UAV to provide reliable mobile network connectivity by considering the ground users' movement.

A. RELATED WORKS

Many researches propose strategies of deploying UAV by optimizing objective functions that have different aims [1], namely, minimizing the transmit power of UAVs [3], [4], maximizing the wireless coverage of UAVs [5], minimizing the number of UAVs required to perform a given task [6], and optimizing UAV trajectory [7]. Technical issues, such as endurance time is an important issue to be addressed as the duration of UAV mission is lengthened [1]. Therefore, the efficient 3D deployment of UAV strategies to minimize

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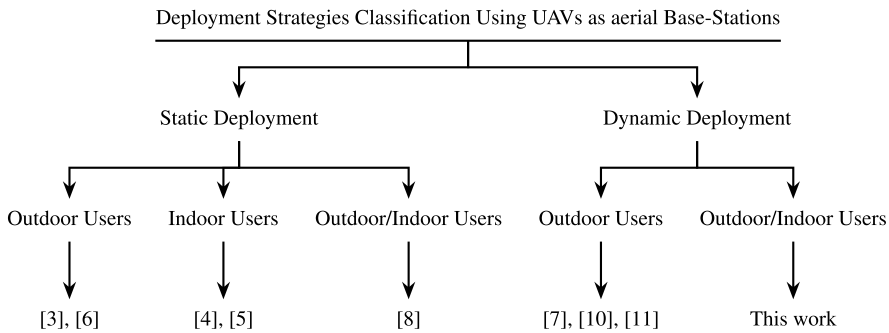


FIGURE 1. Deployment strategies classification using UAV as an aerial base station.

the UAV transmit power in providing wireless coverage to the ground users, have been addressed in [3]–[9].

The deployment of UAV as an aerial base station in providing wireless coverage to the ground users can be classified into two categories, based on either UAV in static condition or UAV in moving condition, which may be referred to as static deployment, or dynamic deployment, respectively. Within each of the category, the research can be further classified based on the locations of the ground users. More specifically, the UAV is deployed to provide wireless coverage for either outdoor ground users only, indoor ground users only or outdoor and indoor ground users simultaneously, as illustrated in Figure 1.

In the case of static UAV deployment, there are many works that consider the UAV as an aerial base station in providing wireless coverage for outdoor ground users only [3], [6]. More specifically, the authors in [3] studied the UAV deployment in an optimal altitude that minimizes the required UAV transmit power and maximizes the wireless coverage. In [6], the strategy of deploying multiple UAVs with the objective of minimizing the required UAV transmit power in providing wireless coverage over a large area was studied. In this paper, it was proposed to utilize Circle Packing Theory (CPT) in order to find the minimum number of UAVs to be deployed in such that the coverage area and coverage density were maximized.

Whilst, authors in [4], [12], [13] studied the UAV deployment strategies as an aerial base station in providing wireless coverage for indoor ground users only. More specifically, they utilized the Outdoor-to-Indoor path loss model presented in [14] to find an efficient 3D UAV location that minimizes the total UAV transmit power required to provide wireless coverage indoor users during disaster situations. In [5] the UAV deployment strategy in finding the minimum number of UAVs required to provide wireless coverage for indoor users only was presented. Meanwhile, the static UAV deployment that provides coverage for both indoor and outdoor users are presented in [8]. More specifically, in [8] the Air-to-Ground (ATG) path loss model of [15] and the Outdoor-to-Indoor path loss model [14] were utilized in finding the efficient 3D placement as an aerial base station that minimized the UAV transmit power.

However, some of the works on the UAV deployment strategies that consider dynamic scenarios can be found in [7], [9]–[11], [16]. The authors in [7], studied UAV trajectory optimization problem that addressed the energy-efficiency of UAVs. This work proposed a theoretical model of propulsion energy consumption for a fixed-wing UAV that considers both its velocity and acceleration. Optimal UAV trajectories that consider a dynamic network scenario was studied in [16]. Furthermore, this work utilized quantization theory as an analytical tool to characterize the achievable performance of the UAVs, as mobile aerial base stations.

For the dynamic UAV deployment scenario, the works in [9], [11], optimized 3D UAV placement by considering the users' movement. This is because user movement can affect the wireless network performance if the optimized UAV placement is determined based on a specific configuration only. In [9], the dynamic UAV deployment problem was considered in the context of multiple UAVs as aerial base stations for data collection from the ground Internet of Things (IoT) devices in an uplink communication scenario. The proposed algorithm aimed for an optimized 3D trajectory for each UAV with the objective of minimizing the total power used for the UAVs mobility. In this work, the IoT active devices were considered to exhibit beta distribution. Similarly, the dynamic multi-UAVs deployment was also considered in [10]. More specifically, in [10] the authors considered problem in finding optimal trajectory paths with the objective of maximizing the minimum average sum rate by jointly optimized the power allocation and paths of multi-UAVs, user association and scheduling. Whilst, in [11], the authors used random walk model to represent the users' movement, and proposed the solution to find the 3D positioning of aerial base stations using reinforcement learning, which is known as Q-learning.

A more comprehensive survey and tutorial on UAV communications, namely, cellular-connected UAVs and UAV-assisted wireless communications, which highlights the deployment of UAVs as an aerial communication platform for outdoor users is presented in [17]. With regards the dynamic

UAV deployment scenario, a unified and general mathematical framework for designing a joint UAV communication and trajectory, is also presented in [17]. However, these studies assumed that all users are located outdoor. More specifically, to the best of our knowledge, all previous studies on the dynamic UAV deployment do not consider the case of providing wireless coverage for indoor users.

Therefore, in this paper we study the dynamic deployment of a single UAV as an aerial base station in providing wireless coverage for a rescue team in search and rescue (SAR) operation during emergency cases or natural disasters. The UAV is deployed as an aerial base station in providing continuous wireless coverage for mobile outdoor and indoor users. More specifically, in this work we propose an algorithm to find an efficient UAV trajectory in providing wireless coverage for mobile users that minimizes the total UAV transmit power and satisfy the minimum user's required data rate. Furthermore, we consider two different user's movement, namely individual movement and group movement. More specifically, the random waypoint [18] is used to model the individual movement, whilst, the group movement is modeled using reference point group mobility model (RPGM) [19]. The random waypoint model is used to represent the movement of the rescue team member that is located indoor, whilst, the RPGM model is used to represent the movement of the rescue team members that are located indoor and outdoor.

B. PAPER CONTRIBUTIONS

The contributions of this work are summarized as follows:

- Two different user's mobility models are used to represent the rescue team member's movement inside the targeted coverage area. The outdoor rescue team members are considered to move in a group with RPGM model. Whilst, the indoor rescue team members are considered to move individually and in a group with random waypoint and RPGM models, respectively.
- The efficient UAV trajectory algorithms are developed for the deployment of a single UAV as an aerial base station in providing wireless coverage for mobile outdoor and indoor users. More specifically, particle swarm optimization (PSO) and genetic algorithm (GA) are utilized to find the efficient UAV trajectory that provides continuous wireless coverage for the mobile rescue team members in a SAR operation. The problem is formulated with the objective of minimizing the required UAV transmit power that satisfies the minimum users' data rate while considering the outdoor and indoor users' movement with random waypoint and RPGM models.
- The optimal UAV trajectory algorithm is developed using brute-force search space method. The employment of heuristic algorithms in finding an efficient UAV trajectory that minimizes the required UAV transmit power while considering the users' movement significantly reduced the execution time, and hence, significant reduction of computation complexity, when compared with the optimal UAV trajectory algorithm.

The rest of this paper is organized as follows. Section II presents the system model which includes the ground users' mobility models and the communication channel models for outdoor and indoor users. In Section III, the problem of finding an efficient trajectory of UAV to provide a continuous wireless coverage for mobile users is formulated as an optimization problem. Next, Section IV presents two different solutions, namely the optimal and efficient UAV trajectory algorithms based on an exhaustive search method and heuristic algorithms, respectively. The simulation results are presented in Section V-A. Whilst, Section V-B discusses the main observations obtained from the simulation results. Finally, the conclusions are presented in Section VI.

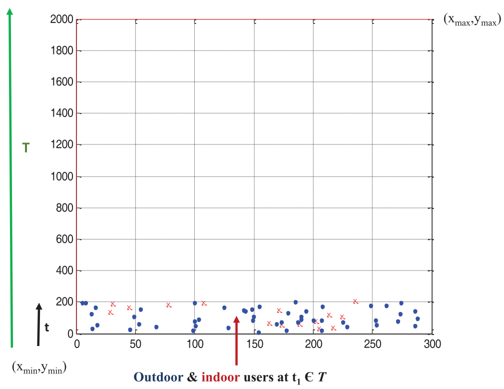


FIGURE 2. System settings of a subarea coverage using a single UAV. The dimensionalities of the axes are meters.

II. SYSTEM MODEL

Consider a rectangular geographical area where the natural disaster occurs, $\mathbb{D} \subset \mathbb{R}^2$ that is divided into N subareas, denoted as $\mathcal{S}$, with minimum and maximum points of (x_{min},y_{min}) and (x_{max},y_{max}), respectively as illustrated in Figure 2. Each subarea, $\mathcal{S}$ is further divided into n sub-regions, namely, $k_1, k_2, k_3, \ldots k_n$ where k_n denotes a sub-region with n denoting the index of each sub-region. Within each sub-region, k_n, there are M_{out} of outdoor mobile ground users and M_{in} of indoor mobile ground users, that are uniformly distributed.

In this model, it is considered that a single UAV serves as a mobile aerial base station in order to complete SAR operation for each subarea, $\mathcal{S}$. The 3D location of UAV$_i$ is represented by (x_i, y_i, z_i) where (x_i, y_i) is the 2D placement of UAV$_i$ and z_i is the altitude of UAV$_i$. The UAV can dynamically move to serve the users in the downlink communication link using frequency division multiple access (FDMA) as the channels access technique. In this model, it is assumed that the UAV allocates equal channel bandwidth to each mobile ground user, in order to avoid interference. Whilst, the ground users are considered to move individually and in a group, with the random waypoint and RPGM models, respectively.

More specifically, in the RPGM model, all users in the group follow the motion of the reference point (RP) as explained in Section II-A.2. Furthermore, in this proposed model, we assume that the users are distributed uniformly around the RP within a given rectangular area, referred to as a sub-region, k_n. Additionally, based on this model the users move in a group from one rectangular sub-region to another rectangular sub-region, and the behaviour of the group motion is defined by the RP motion parameters. Similarly, we also assume the users that move individually with the random waypoint model are also distributed uniformly and confined within the rectangular sub-region, at each time step. Thus, this proposed method is limited to the scenario in which users are distributed uniformly within a specific sub-region, at each time step.

A. GROUND USERS' MOBILITY MODELS

Mobility models describe different types of user's moving behaviours or node mobility patterns within a variety of network scenarios. There is a large variety of mobility models in the literature [18]–[22], which can be categorized into individual user/node movement models and group movement models. The mobility models such as Random Walk or Brownian motion, Probabilistic Random Walk [20], Random Waypoint [18], Random Direction [21], Gauss-Markov [20] and Weighted Waypoint [22] are among the models that describe individual user moving behaviours. Whilst, examples of the mobility models that describe group moving behavior are RPGM [19], Column Mobility Model, Nomadic Mobility Model, and Pursue Mobility Model [20]. As mentioned earlier, in this paper, we consider the ground users are the rescue team members in SAR operation that move individually, as well as, in a group. More specifically, it is considered that some of the indoor rescue team members move individually with random waypoint model, whilst, some of them move in a group with RPGM model. Meanwhile, the rescue team members that are located outdoor move in a group with RPGM model.

1) RANDOM WAYPOINT

In the random waypoint mobility model, the mobile users move freely and randomly without any restrictions. It is an extension of random walk model. More specifically, the speed, direction and destination are chosen randomly and independent of other users [18]. In this mobility model the users are initially distributed randomly. The users' movement in this mobility model can be described as follows: 1) Each user randomly chooses the destination, which is referred to as waypoint; 2) The user's velocity is chosen randomly from the interval of [Speed_min, Speed_max] that is uniformly distributed; 3) Each user moves towards its chosen destination; 4) After the user reaches the destination, it stopped for a constant pause time. This movement describes the user's behaviour that stays at a location for a certain time before it moves to a new destination. 5) Then, the user chooses the next destination and step 1-4 are repeated again until the users reach stationary distribution [23].

2) REFERENCE POINT GROUP MODEL

The RPGM model [19] is one of the group mobility models. In this model, each group has its logical reference center, which is referred to as reference point (RP), and all users in the group follow the RP movement. More specifically, the motion of group RP defines the behavior of the group motion, including other motion parameters such as speed, location, direction and acceleration. Therefore, the trajectory of the group is determined based on the logical reference center motion. The users are distributed uniformly around the reference center within the geographical area of the group. At each time step, the users' movement within the geographic scope of the group follow the RP and the locations of each node is randomly placed around the RP.

The RPGM mobility model can be used to describe users' movement for many scenarios, such as in military battlefield communications and during disaster recovery in SAR operations. In these scenarios, users move towards a target with a common objective, thus creates a collective movement of all users.

The RPGM consists of reference point (reference center) and users within the area, which may be referred to as group nodes. The key elements of RPGM model can be described as follows:

- Reference point: In this model, the reference point leads the group movement, and it represents the motion pattern for the group. Vector $\overrightarrow{V_{g(t)}}$ represents the reference point movement of the group at time t and speed s. The path of the vector $\overrightarrow{V_{g(t)}}$ can be chosen randomly or based on predefined trajectory. In this work, the path of the vector based on a predefined trajectory is considered.
- Group nodes: Group nodes refer to users within the geographical area of the group. For node i, at time t, its motion vector $\overrightarrow{V_{i(t)}}$ can be described as follows:
$$\overrightarrow{V_{i(t)}} = \overrightarrow{V_{g(t)}} + R_i(t) \tag{1}$$
where $R_i(t)$ is the group motion vector of node i, and $\overrightarrow{V_{g(t)}}$ is the reference point motion vector.

Figure 3 shows an example of RPGM model scenario. In this figure, the reference point, RP moves based on a predefined trajectory from RP1 at time t_1 to RP2 at time t_2. More specifically, RP1, RP2, ... RPi, are new reference point with i denoting the index of each check point. The new check point at time t_2, the locations for group nodes are generated based on random distribution function around RP2. The group continues to move towards RP3, RP4 and RP5, and at each of the new check point, the group nodes' location are also generated based on random distribution function within the geographic scope of the group.

B. CHANNEL MODELS

1) AIR TO GROUND CHANNEL MODEL

In this paper, the ATG path loss of [15] is utilized. The ATG path loss is modelled by considering the probability of LOS

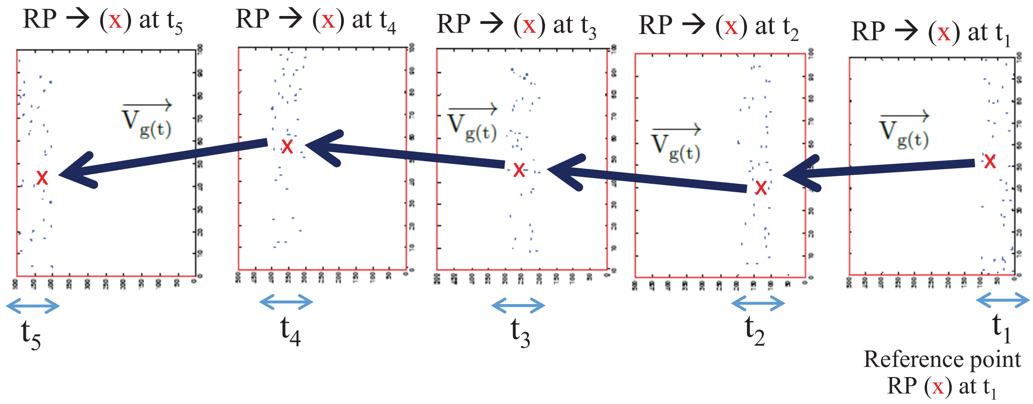


FIGURE 3. An example of the RPGM model with predefined trajectory.

and Non-Line of Sight (NLOS) links. The probability of LOS can be formulated as:

$$P_{LOS} = \frac{1}{1 + \alpha\ exp(-\beta[\theta - \alpha])} \tag{2}$$

where α and β are two constants depending on the environment type. θ is the elevation angle of the UAV, where $\theta = \sin^{-1}(\frac{h}{d})$, h is the altitude of UAV, and d is the distance between ground user and the UAV, where $d = \sqrt{r^2 + h^2}$, with r denoting the distance between UAV projection at xy plane and the ground user, as shown in Figure 4. Whilst, the NLOS probability is given by $P_{NLOS} = 1 - P_{LOS}$.

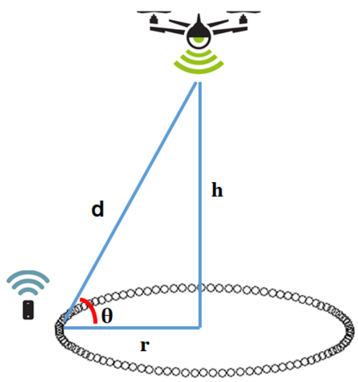


FIGURE 4. UAV Coverage Zone.

The ATG pathloss in dB can be represented as [15]:

$$PL_{out}(dB) = FSPL + P_{LOS} \times \eta_{LOS} + P_{NLOS} \times \eta_{NLOS}, \tag{3}$$

The free space pathloss, FSPL is given as:

$$FSPL = 20log(\frac{4\pi f_c d}{c}) \tag{4}$$

where f_c is the carrier frequency, c is the speed of light, whilst η_{LOS} and η_{NLOS} are the average additional loss to the free space propagation for LOS and NLOS links, respectively, which depend on the environment.

2) OUTDOOR TO INDOOR CHANNEL MODEL

In the case of providing wireless coverage for rescue team members that are located indoor, the path loss model for Outdoor-to-Indoor certified by ITU [14] is considered, which can be described as:

$$PL_{in}(dB) = PL_F + PL_B + PL_{IN}, \tag{5}$$

where the free space path loss, PL_F is given as $20log(d_{3d}) + 20log(f_c) + a_1$, the building penetration path loss, $PL_B = a_2 + a_3 \cdot (1 - cos\theta)^2$, and the indoor path loss, PL_{IN} is given by $a_4 \cdot d_{2d_{in}}$, whilst d_{3d} is the euclidean distance between the indoor user i and the UAV, f_c is the carrier frequency, θ is the incident angle, and $d_{2d_{in}}$ is the 2D indoor distance between user i and the UAV, a_1, a_2, a_3, a_4 are constant values that depend on the environment. In this work, $a_1 = 32.4$, $a_2 = 14$, $a_3 = 15$, $a_4 = 0.5$ are used.

III. PROBLEM FORMULATION

In this problem, we consider a single UAV that provides continuous wireless coverage to M_{out} outdoor and M_{in} indoor ground rescue team members within a subarea that has a rectangular shape with the minimum and maximum points of (x_{min},y_{min}) and (x_{max},y_{max}), respectively. Here, we analyze the SAR operation that takes place within a time interval of $[0, T]$. The rescue team reaches y_{max} at time T, where T is the time period required to complete the SAR operation within a subarea. As mentioned earlier, there is n sub-regions in each subarea, $\mathcal{S}$. Therefore, there are $T = n \times t_n$ where n is the number of sub-regions for each subarea and t_n is the time required for the SAR operation to complete within each sub-region with n denoting the index of each sub-region.

The outdoor and indoor rescue team members are distributed uniformly within a sub-region with the minimum and maximum points of (0,y_{t_n}) and (x_{max}, $y_{t_{n+1}}$). More specifically, at each time step t_n, the rescue team members move from y_{t_n} to $y_{t_{n+1}}$, with n denoting the index of each sub-region. Figure 2 illustrates these parameters, whilst, the blue dots denote outdoor rescue team members, and red crosses denote the indoor rescue team members.

The total required UAV transmit power at time t that satisfies the minimum data rate r for all rescue team members can be formulated as:

$$P_t(t) = \sum_{i=1}^{M_{out}}[(2^{\frac{r.M_{out}}{B}} - 1) \times N \times PL_{out\_i}(t)] + \sum_{j=1}^{Min}[(2^{\frac{r.M_{in}}{B}} - 1) \times N \times PL_{in\_j}(t)], \quad (6)$$

where B is the total available bandwidth, PL_{out_i} is the path loss between the UAV and the outdoor rescue team member, i and PL_{in_j} is the path loss between the UAV and the indoor rescue team member, j, whilst, N is the noise power.

Our objective is to find an efficient UAV trajectory in providing continuous wireless coverage for rescue team members by minimizing the total required UAV transmit power in such that the required data rate is satisfied. This trajectory allows UAV to track the rescue team members' movement during SAR operation, while, it operates as an aerial base station at an efficient 3D placement.

As we can see in Equation (6) the terms $(2^{\frac{r.M_{out}}{B}} - 1) \times N$ and $(2^{\frac{r.M_{in}}{B}} - 1) \times N$ are constant, so the formulated problem can be simplified as follow:

$$\underset{x_u{}^t, y_u{}^t, z_u{}^t : t \in T}{\text{minimize}} \; PL^t_{total} = \sum_{i=1}^{M_{out}} PL^t_{out\_i} + \sum_{j=1}^{M_{in}} PL^t_{in\_j} \quad (7a)$$

$$\text{subject to} \; \sum_{i=1}^{M_{out}} PL^t_{out\_i} + \sum_{j=1}^{M_{in}} PL^t_{in\_j} \leq PL_{max} \quad (7b)$$

$$0 \leq t \leq T \quad (7c)$$

$$x_{min} \leq x_{i_{UAV}}(t) \leq x_{max} \quad (7d)$$

$$y_{min} \leq y_{i_{UAV}}(t) \leq y_{max} \quad (7e)$$

$$z_{min} \leq z_{i_{UAV}}(t) \leq z_{max} \quad (7f)$$

The first constraint guarantees that the total path loss does not exceed the maximum acceptable path loss, PL_{max}. The second constraint ensures that the time slot for each sub-region does not exceed the total time, T. The last three constraints ensure that the 3D placement x_u, y_u and z_u of UAV is within the range of the minimum and maximum values. In this contribution, we propose the following heuristic approach to solve this problem:

1) The subarea $\mathcal{S}$ is divided into n sub-regions $k_n = 1, 2, \ldots, n$, where k_n denotes a sub-region with n denoting the index of each sub-region. Each sub-region, k_n has a minimum and maximum points of $(0, y_{t_n})$ and $(x_{max}, y_{t_{n+1}})$, respectively. More specifically, the length of each sub-region, is defined as $l_n = y_{t_{n+1}} - y_{t_n}$. Then, the location of rescue team members at each time step t is generated using the RPGM model for outdoor users and using the random waypoint and RPGM models for indoor users.
2) For each sub-region, k_n, a simplified optimization problem of Equation (8a) is used, to find an efficient UAV 3D placement that minimizes the total transmit power in providing wireless coverage for all rescue team members within the sub-region.
3) The heuristic approach to solve the optimization problem of Equation (8a) is as follows: If the UAV total transmit power is less than the threshold value, the length of the sub-region, l_n will be increased by 10 m. This process will be repeated. However, if the UAV total transmit power is greater than the threshold value, the length of the sub-region, l_n is decreased by 5 m. These processes will be repeated until the total UAV transmit power is less than equal to the threshold UAV transmit power, which is 1.0 *watt* in this system model.

The optimization problem of Equation (7a) can also be represented as follows:

$$\underset{x_u{}^t, y_u{}^t, z_u{}^t : t \in T}{\text{minimize}} \; P^t_{t_{total}} \quad (8a)$$

$$\text{subject to} \; P^t_{t_{total}} \leq P_{t_{UAVmax}} \quad (8b)$$

$$(x_{min}, y_{min}, z_{min}) \leq (x_u{}^t, y_u{}^t, z_u{}^t) \quad (8c)$$

$$(x_u{}^t, y_u{}^t, z_u{}^t) \leq (x_{max}, y_{max}, z_{max}) \quad (8d)$$

where the minimum UAV transmit power over a duration time, t to provide coverage for all rescue team members in order to complete SAR operation within a sub-region, is given as follow:

$$P^t_{t_{total}}(min)(dB) = P^t_{r_{th_{total}}}(dB) + PL^t_{total} \quad (9)$$

$$P^t_{r_{th_{total}}}(dB) = N + \gamma_{th} \quad (10)$$

where $P^t_{r_{th\_total}}$ is the minimum power received by all users. N is the noise power and γ is the SNR threshold value. Clearly, the optimization problem to find the optimal UAV trajectory is NP-hard problem [24]. Therefore, heuristic algorithm such as genetic algorithms (GA) [25], particle swarm optimization (PSO) [26], and K-means with ternary search [8], can be utilized to solve this optimization problem, which are presented in the next section.

IV. UAV TRAJECTORY ALGORITHMS

In this section, we present two different approaches in solving the problem of finding an efficient UAV trajectory in providing continuous wireless coverage for rescue team members during SAR operation. More specifically, we utilize an exhaustive search method using brute-force search space algorithm, as well as, heuristic algorithms using PSO and GA algorithms to solve the optimization problem formulated in Section II. The pseudo code and the flowchart of the proposed algorithms are also presented in this section.

A. OPTIMAL TRAJECTORY ALGORITHM

In this paper, the brute-force search space algorithm is used to find the optimal UAV trajectory that minimizes UAV transmit power. This algorithm scans all 3D points in the coverage space of UAV (inside each k_n). The 3D space dimension is (0, y_{t_n}, z_{kn_min}) and (x_{max},$y_{t_{n+1}}$,z_{kn_max}), where x and y is the 2D dimension of the sub-region, and z is the UAV altitude. Then, the algorithm finds the required transmit power at each 3D point (location) in the space. Hence, the point that results in the minimum required transmit power can be determined, which can also be referred to as the optimal 3D UAV placement. The resulting optimal 3D placement is then compared to the efficient solution that is found using heuristic algorithms, namely PSO and GA. The main drawback of the brute-force search space algorithm is its computational complexity of $\mathcal{O}(n^3)$. More specifically, this algorithm takes much higher execution time than the proposed heuristic algorithms. In this scenario, the whole 3D search space (x, y, z) is scanned every time slot t for each sub-region to find the optimal UAV trajectory. This takes a long time compared to the heuristic algorithms. Algorithm 1 presents the brute-force search space algorithm.

Algorithm 1 Brute-Force Search Space Algorithm

Optimal UAV Trajectory
1: **Input:**
(h_{min}, h_{max}): minimum and maximum UAV altitude.
(x_{min}, x_{max}), (y_{min}, y_{max}): minimum and maximum 2D sub-area dimensions.
2: **Initialiaztion:** total_pathloss=0;
3: **For** h= h_min : 1 : h_max
4: **For** x= x_min : 1 : x_max
4: **For** y= y_min : 1 : y_max
5: for All users (U):
Find the: total_pathloss;
See equations (3) and (5)
end
end
end
6: If (total_pathloss(x) $\leq$ total_pathloss(x+1))
then $min\_total\_pathloss(x) = total\_pathloss(x)$;
7: **else** $min\_total\_pathloss(x) = total\_pathloss(x+1)$;
end
8: **Repeat** until finish all values of h, x and y; The optimal 3D placement of UAV (x, y, h) at Minimum pathloss $=$ $min\_total\_pathloss(x)$.

B. EFFICIENT TRAJECTORY ALGORITHMS

In this contribution, PSO and GA are utilized to find the efficient trajectory for an UAV that provides continuous wireless coverage for the rescue team members during their movement in the SAR operation.

1) PARTICLE SWARM OPTIMIZATION (PSO) ALGORITHM

In [26], the authors proposed PSO which is an optimization technique based on the swarm intelligence paradigm, and social behavior of animals such as schools of fish and flocks of birds. PSO is a nature inspired evolutionary optimization method used to solve computationally complex and hard problems. In PSO, a swarm of n particles communicate using search directions with other particles either directly or indirectly over the search space to find a global best optimum. During each iteration, all particles update their location and velocity for better positions according to its experience and its neighbours experience.

PSO is initialized with a group of random particles (solutions) for all particles position and velocity. After that, in every iteration the velocity and local best location for each particle are updated according to Equations 11 and 12, respectively. Moreover, the global best location is also updated. Figure 5 presents the flowchart of PSO algorithm.

$$Vi(t+1) = V_i(t) + (c1 * rand()) * (P_i^{BestLocation}(t) - P_i(t)) + (c2 * rand()) * (P^{GlobalBest}(t) - P_i(t)), \quad (11)$$

where $V_i(t+1)$ is the particle velocity at $t+1$, whilst, $c1$, and $c2$ are the acceleration coefficients for local and global best respectively. The $rand()$ function is a pseudo-random number generator having $\in [0,1]$, $P_i(t)$ is the position of the i_{th} particle, $P_i^{BestLocation}(t)$ is the best known position of the i_{th} particle at time t, and $P^{GlobalBest}(t)$ is the swarm best position known.

The particle position is updated using the following equation:

$$P_i(t+1) = P_i(t) + V_i(t+1). \quad (12)$$

In this work, the computational complexity refers to computational steps in a single iteration of the PSO algorithm. More specifically, each iteration consists of a fitness function evaluation of each particle of n population, as well as, the velocity and position update, p. Hence, considering the worst-case scenario, the computational complexity can be denoted as $\mathcal{O}(np)$.

2) GENETIC ALGORITHM (GA) ALGORITHM

A GA is a search meta heuristic algorithm inspired from Darwin's natural evolution and natural selection theory. It can be used to find an efficient solution for solving non-convex optimization problems, which is also referred to as NP-hard optimization problems [27], [28]. In this work, GA is applied to find an efficient UAV trajectory that minimizes the UAV transmit power. In this section, the phases of a GA invoked to find an efficient solution for the optimization problem is presented.

a: INITIAL POPULATION

To begin the GA process, a set of individuals which is called initial population N_{pop} is created. Each individual represents a legitimate solution to the given optimization problem. An individual should be characterized by a set of parameters such as a combination of numbers, alphabets or characters known as chromosome (legitimate solution). In our specific problem, each individual in the population is represented by the 3D UAV placement $(x_{UAV}, y_{UAV}, z_{UAV})$, as the chromosome.

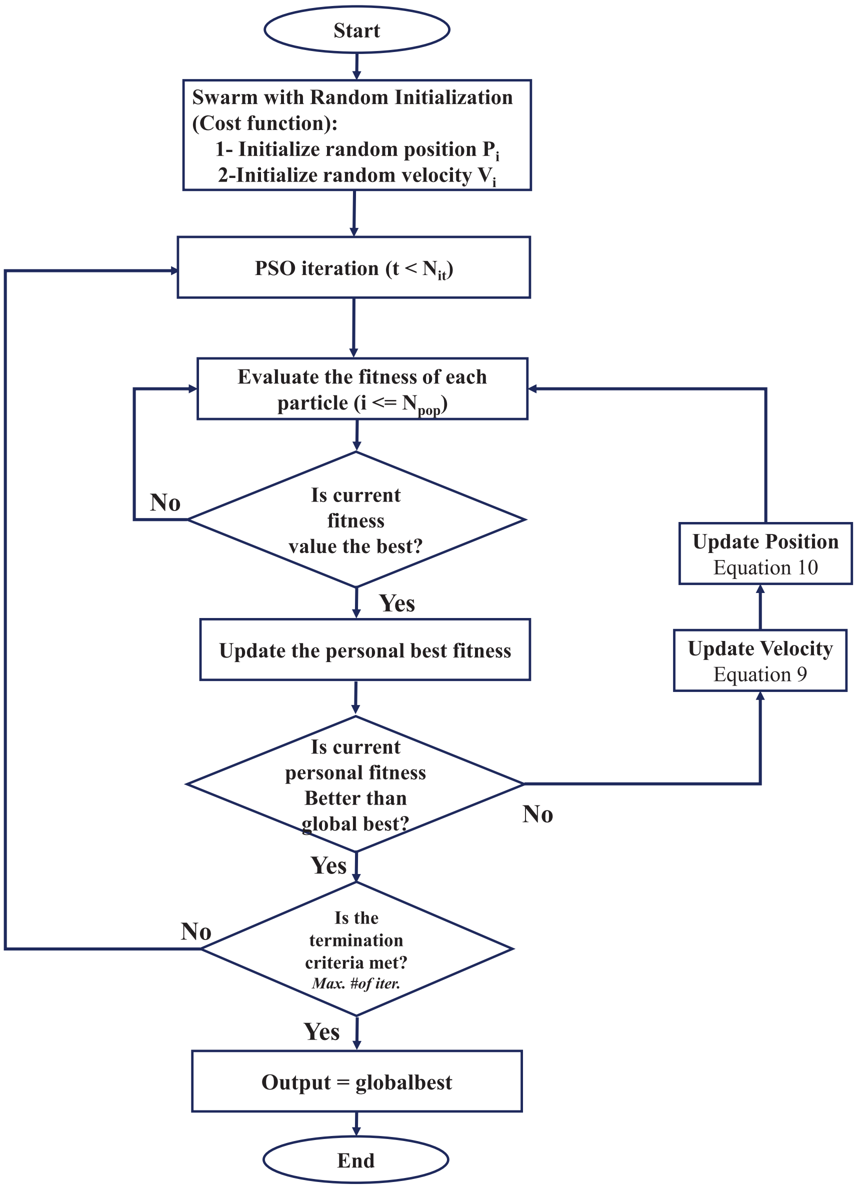


FIGURE 5. Flowchart for finding an efficient UAV 3D placement in each sub-region using PSO.

b: FITNESS FUNCTION

The fitness function is used to evaluate each individual in the population. The GA fitness function repeatedly calculates the fitness value associated with each individual. In each iteration, a fitness score is set to each individual. Then, these values are sorted based on their fitness scores. Fitness score is then used in selection phase for reproduction of the next generation. Individual with higher fitness score has higher probability to be selected.

c: SELECTION

In this phase, a group of the fittest individuals is selected for creating the next generation. These individuals are selected based on their fitness score values, which are also referred to as parents. These parents inherit their genes to the offspring's in the next generation. This selection strategy is also referred to as tournament selection strategy. More specifically, k-individuals are selected, then the tournament is run to select the fitness individuals f, that have the best fitness score among k-individuals. The top score individuals are then selected to generate the next generation of k-individuals.

d: CROSSOVER

One of the basic operators in GA is crossover. In order to create offspring, the genes of parents are exchanged among themselves until the crossover point is reached. Then, the new offspring form the next generation and are added to the population.

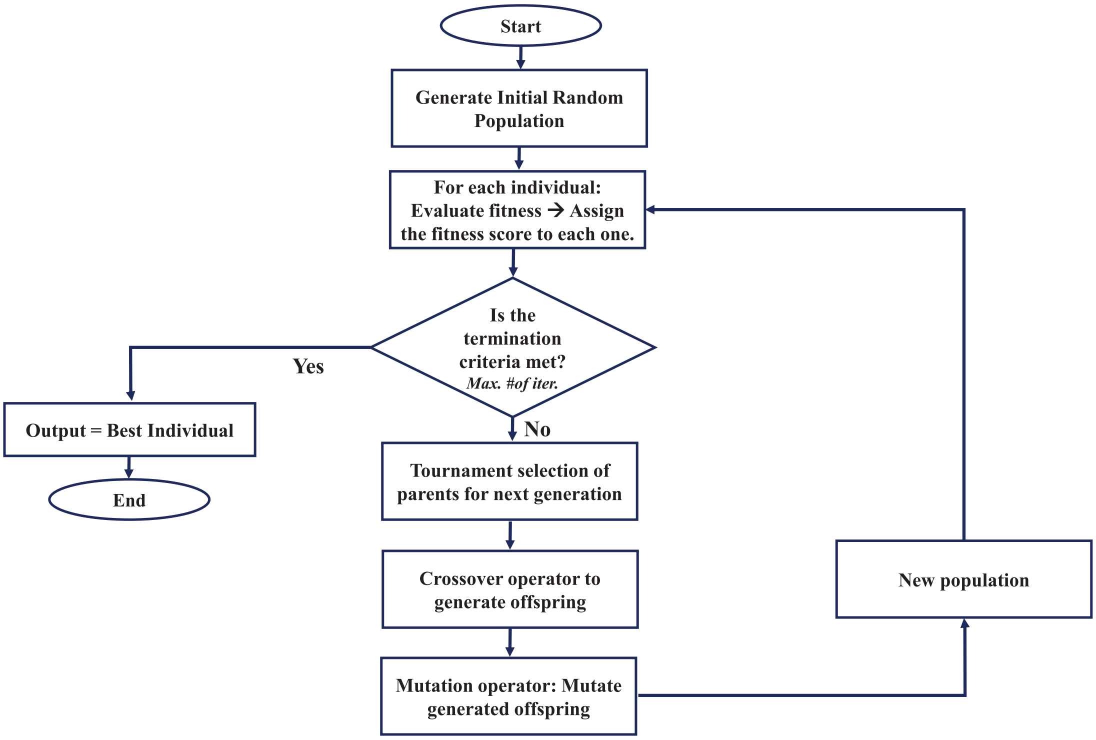


FIGURE 6. Flowchart for finding an efficient UAV 3D placement in each sub-region using GA.

e: MUTATION

Mutation phase occurs in each iteration to maintain the diversity of the genetic population and prevent premature convergence, such as trapped into local optimum solutions. Mutation randomly changes the new offspring. In this work, a bit flip mutation operator is used, where one or more random bits (genes) are selected and flipped. Figure 6 shows the flowchart of the GA algorithm.

Similar to the definition of computational complexity for the PSO algorithm presented in Section IV-B.1, the computation complexity of the GA algorithm also refers to computational steps in a single iteration. More specifically, in the GA algorithm the fitness function of each particle of n population will be evaluated, then, the tournament selection to select m individuals that have the best fitness score, to become parents of the new generation of m individuals using the crossover and mutation process. More specifically, in the tournament selection, it takes $\mathcal{O}(log(m))$ operations, after building the initial tournament in $\mathcal{O}(m)$. Thus, considering the worst-case scenario, the computational complexity of the GA algorithm can be denoted as $\mathcal{O}(n.mlog(m))$.

V. SIMULATION RESULTS AND DISCUSSIONS

A. SIMULATION RESULTS

We consider the deployment of a single UAV as an aerial base station to provide continuous wireless coverage for a rescue team to complete SAR operation within a subarea $\mathcal{S}$, as introduced in Section III, while considering continuous wireless coverage for both mobile outdoor and indoor rescue team members.

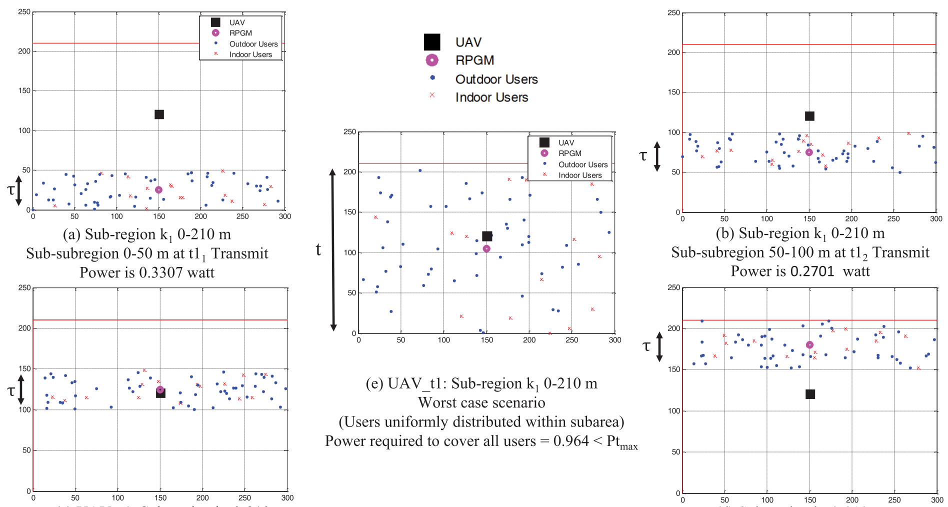
This section presents the simulation results of the proposed PSO and GA algorithms to find an efficient UAV trajectory that considers the rescue team members moving individually and in a group, with the random waypoint and RPGM mobility models, respectively, as described in Section II-A. More specifically, the proposed algorithms are invoked to find an efficient UAV trajectory with the objective of minimizing its required transmit power that satisfies the user's minimum data rate. The parameters used in the simulations are outlined in Table 1.

The dimension of the subarea is 300 $m \times$ 2000 m, and the overall time required to complete the SAR operation in each subarea $\mathcal{S}$ is denoted as, T. Each subarea, $\mathcal{S}$ is divided into n sub-regions, each sub-region has the dimensions of 300 $m \times l_n$, where l_n is the length of each sub-region $\in \mathcal{S}$ with n denoting the index of each sub-region. The velocity of the outdoor users movement is 0.41 m/s, and the time required for the SAR operation to complete within each sub-region is denoted as t, which is also referred to as time step inside each sub-region.

Figure 7 illustrates a scenario of SAR operation within a specific sub-region, k_1 with a fixed UAV location. In this scenario, we consider the rescue team moves from each sub-subregion to another sub-subregion at velocity of 0.41 m/s, as illustrated in Figure 7(a)-(d). In this case, a sub-region is divided into several sub-subregions, as illustrated in Figure 7(a)-(d). The required UAV transmit power to serve

TABLE 1. SIMULATION AND SYSTEM PARAMETERS.

Simulation Parameters			System and Algorithms Parameters		
Subarea ($\mathcal{S}$) $dimensions$	(x_{max}, y_{max})	$(300\ m, 2000\ m)$	Carrier frequency	f_c	2 GHz
UAV altitude	Z_{min}	$60\ m$	Noise power	Np	-100 dBm
Number of Outdoor users	M_{out}	50	Data Rate	r	1 Mbps
Number of Indoor users	M_{in}	15	Total Bandwidth	B	50 MHz
Rescue mission period	T	$\simeq 80\ min$	Max. UAV transmit power	$Pt_{UAV_{max}}$	1 $watt$
Outdoor movement velocity	V_i	$\simeq 0.41\ m/sec$	PSO, GA Population size	N_pop	50
Region dimensions	$(x_{r_{max}}, y_{r_{max}})$	$(300m, y(t_n))$	Max # of iterations	N_{it}	PSO=50, GA=100
$\#$ of Subregions k_n inside each $\mathcal{S}$	n	9	Environment parameter	a, b	9.6, 0.28
Time period for each k_n	t_n	Table 2	Environment parameter	η_{LSO}, η_{NLSO}	1, 20
			# of Individuals (selection phase)	$k - individuals$	4



(a) Sub-region k_1 0-210 m Sub-subregion 0-50 m at $t1_1$ Transmit Power is 0.3307 watt

(b) Sub-region k_1 0-210 m Sub-subregion 50-100 m at $t1_2$ Transmit Power is 0.2701 watt

(c) UAV_t1: Sub-region k_1 0-210 m Sub-subregion 100-150 at $t1_3$ Transmit Power is 0.2717 watt

(d) Sub-region k_1 0-210 m Sub-subregion 150-210 m at $t1_4$ Transmit Power is 0.3298 watt

(e) UAV_t1: Sub-region k_1 0-210 m Worst case scenario (Users uniformly distributed within subarea) Power required to cover all users = 0.964 < Pt_{max}

FIGURE 7. (a)-(d): Users movement and distribution inside sub-region k_1 from t_{1_1} to $t_{1_4} \in t_{1_{UAV}}$. (e) Users distribution inside sub-region k_1 (Worst Case Scenario).

all mobile outdoor and indoor rescue team members to complete SAR operation within each sub-subregion is less than 0.4 $watt$. However, Figure 7(e) illustrates the scenario where all users are uniformly distributed within a sub-region, k_1 and the total required UAV transmit power is 0.964 $watt$, which is less than the maximum required UAV transmit power of 1 $watt$.

Figure 8 presents the scenario that is presented in Section III, where we consider the rescue team members are uniformly distributed around a reference point and the rescue team moves from one sub-region to another, at each time step, t_n with n denoting the index of each sub-region. More specifically, Figure 8(a) illustrates the SAR operation within sub-region k_1, where the rescue team members move from $y_{t_n} = 0\ m$ to $y_{t_{n+1}} = 210\ m$ at velocity of 0.41 m/s, hence, taking 8.54 min to complete the SAR operation within the sub-region, k_1. In this case, the rescue team members are distributed uniformly around a reference point of $(150, 105)$, and the 3D UAV placement found is $(152.04, 119.87, 60.0)$ where the total required UAV transmit power is 0.964 $watt$ when it is determined using PSO algorithm. However, when GA algorithm is used, the 3D UAV placement found is $(150.57, 119.58, 62.3)$ and the total required UAV transmit power is 0.991 $watt$ as presented in Table 2.

Table 2 presents the efficient 3D UAV placement and the corresponding minimum required UAV transmit power at each time step t_n using PSO and GA algorithms, as well as, the optimal 3D UAV placement using brute-force search space method. It can be seen that the optimal UAV altitude that minimizes the UAV transmit power is the minimum UAV altitude allowed, which is denoted as z_{min}. In this work, the minimum UAV altitude is 60 m for safety reasons in order to avoid any collisions [29].

The optimal 3D UAV placement using brute-force search algorithm are integers due to the increment of (x, y, z) values by 1 m at each iteration. This is because brute-force search space method has high computational complexity, as described in Section IV-A. Thus, in order to reduce the running and computation time and algorithm computational complexity, the values of (x, y, z) are chosen to be integers within the allowed range of (x, y, z). On the other hand, if the

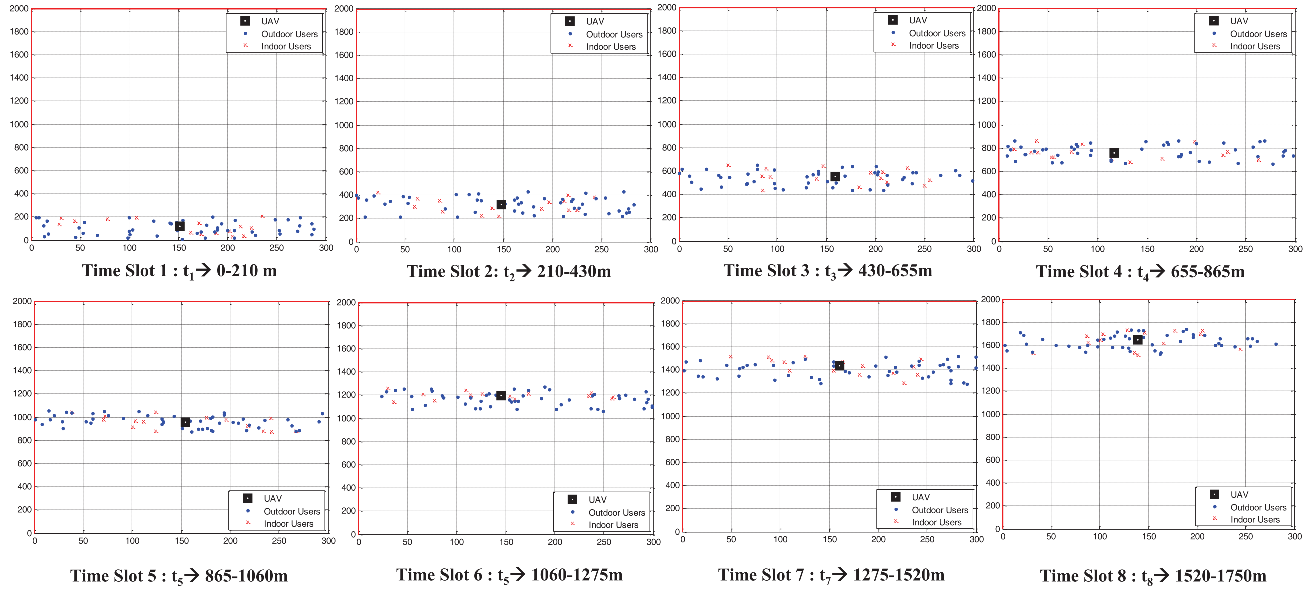


FIGURE 8. Rescue team trajectory within a subarea $\mathcal{S}$ from t_1 to $t_8 \in T$.

TABLE 2. Simulation results for SAR operation within a subarea.

Time Step (t_{n_UAV})	Algorithm	Sub-region Depth (m)	SAR Time Period, t_n (min)	Optimal 3D UAV Placement	3D UAV Placement	Power ($watt$)
t_{1_UAV}	PSO GA	0-210	8.54	[151, 120, 60]	[152.04, 119.87, 60.0] [150.57, 119.58, 62.3]	0.964 0.991
t_{2_UAV}	PSO GA	210-430	8.94	[146, 315, 60]	[148.59, 316.92, 60.0] [148.96, 318.42, 62.3]	0.963 0.991
t_{3_UAV}	PSO GA	430-655	9.14	[157, 554, 60]	[159.65, 555.29, 60.0] [159.33, 554.01, 62.3]	0.982 0.989
t_{4_UAV}	PSO GA	655-865	8.54	[115, 763, 60]	[116.93, 759.36, 60.0] [118.69, 760.33, 62.3]	1.00 1.070
t_{5_UAV}	PSO GA	865-1060	7.92	[154, 955, 60]	[154.58, 955.34, 60.0] [154.14, 955.87,62.3]	0.958 0.971
t_{6_UAV}	PSO GA	1060-1275	8.74	[147, 1195, 60]	[145.54, 1197.60, 60.0] [147.11, 1195.48, 62.3]	0.984 0.999
t_{7_UAV}	PSO GA	1275-1520	9.8	[158, 1436 ,60]	[160.87, 1433.4, 60.0] [161.48, 1431.67, 62.3]	0.979 1.008
t_{8_UAV}	PSO GA	1520-1750	9.92	[140, 1644, 60]	[139.46, 1646.8, 60.0] [140.05, 1644.06, 62.3]	0.984 0.997
t_{9_UAV}	PSO GA	1750-2000	10.16	[183 1881 60]	[183.56, 1881.3, 60.0] [180.63, 1881.03, 62.3]	0.994 1.080

(x, y, z) values are incremented by 0.1 m at each iteration, the execution time and algorithm computational complexity is very high, specifically, it takes more than 3 hours to return the results. Therefore, the optimal 3D UAV locations in Table 2, are integers.

In this scenario, the execution time is used to represent the algorithm computational complexity. It is found that the optimal placement approach using brute-force search space method took about 18.84 sec to find the optimal 3D UAV placement with an increment of (x, y, z) values by 1 m at each iteration with the value of z_{min} of 60. Whilst, the UAV altitude found using the PSO and GA algorithm is in the range of 60 m to 63 m. Whilst, the computation time to find the 3D UAV placement took 0.31 s and 2.07 s only, when using the

TABLE 3. Execution Time for UAV Trajectory Algorithms.

UAV Trajectory Algorithm	Algorithm Complexity	Execution Time in Seconds
Optimal Trajectory Algorithm	$\mathcal{O}(n^3)$	18.84 sec
GA Algorithm	$\mathcal{O}(n.m\log(m))$	2.069 sec
PSO Algorithm	$\mathcal{O}(np)$	0.314 sec

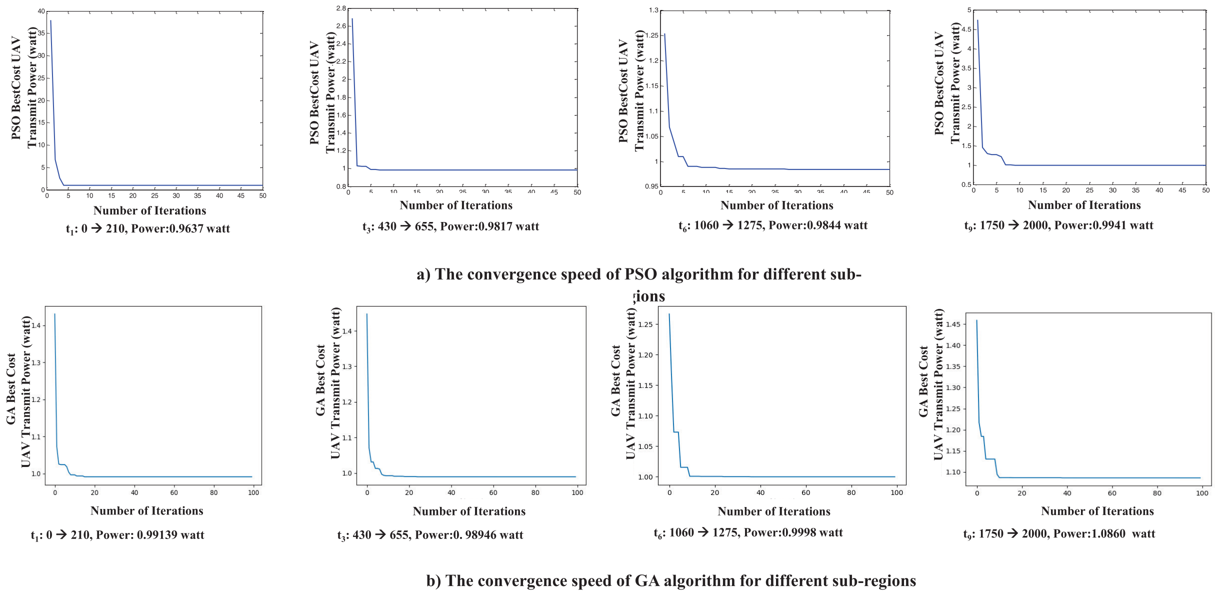


FIGURE 9. The convergence speeds of PSO and GA algorithms for different time steps of t_1, t_3, t_6, and t_9.

proposed heuristic approach namely PSO and GA algorithms, respectively, as presented in Table 2.

More specifically, Table 3 presents the execution time taken in finding the 3D UAV placement for sub-region k_1 using PSO, GA and brute force search space algorithms. It can be seen that the computational complexity for these algorithms that was defined in Section IV are reflected by the execution time taken by each algorithm in finding the 3D UAV placement. It is also observed that the use of PSO and GA algorithms to find the efficient UAV trajectory reduced the execution time by a factor of $\simeq 1/60$ and $\simeq 1/9$ compared to that when using the brute-force search space algorithm, respectively. Whilst, the use of PSO algorithm to find the efficient UAV trajectory reduced the execution time by a factor of $\simeq 1/7$ compared to that when using the GA algorithm. Moreover, the PSO and GA algorithms converge to the efficient solution within a few iterations as can be seen in Figure 9. Thus, the heuristic approach takes less computation time compared to the optimal approach. The convergence speeds of the PSO and GA algorithms for different time steps are shown in Figure 9.

Whilst, Figure 10 shows the optimal UAV trajectory and the efficient UAV trajectory in 2D during SAR mission from t_1 to $t_8 \in T$ using brute-force search space method, PSO and GA algorithms.

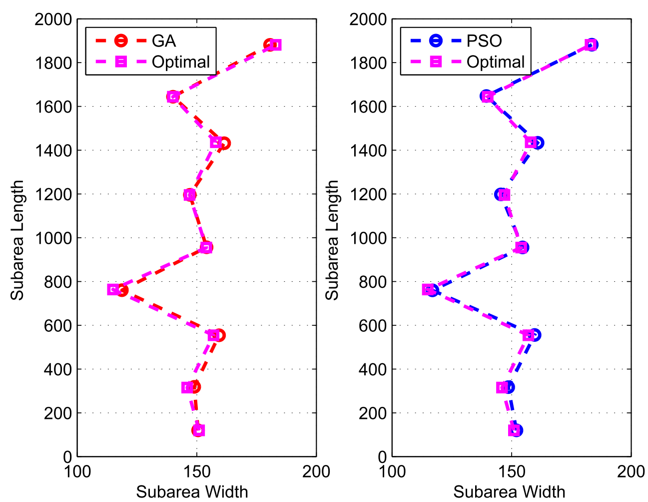
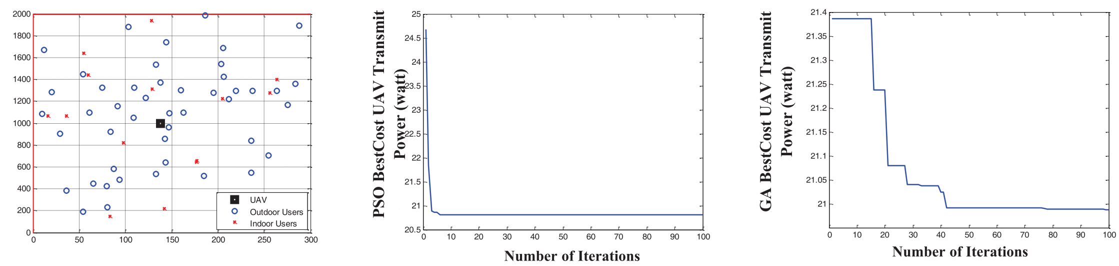


FIGURE 10. Efficient UAV trajectory in 2D during SAR operation from t_1 to $_9 \in T$.

The performance of the dynamic UAV deployment scenario is also compared with the case of the static UAV deployment scenario. In the case of the static UAV deployment scenario, the movement of the rescue team members is not considered. Hence, the rescue team members are considered



(a) Users Uniformly Distributed within Subarea 300 m × 2000 m

(b) Convergence speed for PSO and GA for Subarea 300 m × 2000 m

FIGURE 11. Static UAV deployment scenario (*a*) Users are uniformly distributed within subarea. (*b*) Convergence speed of PSO and GA algorithms.

to be uniformly distributed inside the search subarea, $\mathcal{S}$, instead of within each sub-region, k_n as the scenario considered in the dynamic deployment. Figure 11(a) illustrates the static UAV deployment scenario.

In the static UAV deployment case, the simulation results show that the total UAV transmit power required to provide wireless coverage for all users to complete the SAR operation is 20.814 *watt* with the 3D UAV placement is [138.1893, 995.8992, 60] when using PSO algorithm. Whilst, the required UAV transmit power is 20.9314 *watt* and the 3D UAV placement is [136.8074 958.6295 61.23] when using GA as shown in Figure 11(b).

More explicitly, in the case of static UAV deployment required more than 20 *watt* of the total transmit power compared with the dynamic UAV deployment that required less than 10 *watt* of that to complete SAR operations within subarea $\mathcal{S}$. Thus, the deployment of mobile UAV that can track the rescue team members movement during the SAR operation requires less total transmit power by a factor of about $1/2$ compared to the static UAV deployment scenario.

Moreover, in the case of dynamic UAV deployment scenario, the required UAV transmit power converge to approximately the same values at each time step as we can see in Figure 9.

B. DISCUSSION

In this section, the main observations obtained from the simulation results presented in Section V-A are discussed.

It is observed that the proposed method as illustrated in Figure 7 (e) requires less total transmit power in providing wireless coverage for the rescue team to complete the SAR operation within the sub-region, k_1, compared to the method illustrated in Figure 7(a)-(d). More specifically, in Figure 7(e) the users are uniformly distributed around the RP and the required transmit power to complete SAR operation within the sub-region, k_1 is 0.964 *watt* which is less than the threshold value of 1.0 *watt*. Whilst, in Figure 7(a)-(d) the sub-region k_1 is divided into several sub-subregions and the SAR team moves from one sub-subregion to another sub-subregion. The required transmit power required to complete SAR operation within sub-subregion illustrated in Figure 7(a)-(d) is 0.3307 *watt*, 0.2701 *watt*, 0.2717 *watt* and 0.3298 *watt*, respectively. However, the total required transmit power using this dynamic UAV deployment strategy exceeds the threshold value of 1.0 *watt*, in order to complete SAR operation within sub-region, k_1. Therefore, the dynamic deployment strategy illustrated in Figure 7(e) is invoked in the SAR operation within the subarea, $\mathcal{S}$.

It is also observed that the proposed dynamic UAV deployment requires less total transmit power in providing wireless coverage for the rescue team to complete the SAR operation within subarea, $\mathcal{S}$, compared to the static UAV deployment. More specifically, as illustrated in Figure 11, the static UAV deployment requires total transmit power of about 20 *watt* in providing wireless coverage to the rescue team in order to complete SAR operation within the subarea, $\mathcal{S}$. Whilst, the proposed dynamic UAV deployment requires the total transmit power less than half of that, as illustrated in Figure 8 and Table 2.

The computation complexity of the proposed efficient UAV trajectory algorithms are evaluated in terms of its execution time. It is observed that the UAV trajectory algorithm invoking PSO and GA reduced the execution time by a factor of $\simeq 1/60$ and $\simeq 1/9$ compared to that when using the brute-force search space algorithm, respectively, as summarized in Table 3. Whilst, the UAV trajectory algorithm invoking PSO reduced the execution time by a factor of $\simeq 1/7$ compared to that when using the GA algorithm.

VI. CONCLUSION

In this paper, an efficient UAV trajectory algorithm is proposed for the dynamic deployment of a single UAV as an aerial base station in providing wireless coverage for mobile outdoor and indoor users. More specifically, the algorithm is developed by considering the users' movement in a SAR operation. The outdoor rescue team members are considered to move in a group with RPGM model. Whilst, the indoor rescue team members are considered to move individually and in a group, with random waypoint and RPGM models, respectively. The solution to the problem of finding the efficient trajectory for the dynamic UAV deployment is developed using two approaches, namely, heuristic and optimal approaches. The employment of the heuristic approach, namely PSO and GA algorithms, to find the efficient UAV trajectory reduced the execution time by a factor of $\simeq 1/60$ and $\simeq 1/9$ compared to that when using the brute-force search space algorithm, respectively. Whilst, the PSO algorithm outperformed the GA algorithm in terms of execution time reduction by a factor of $\simeq 1/7$. The performance of the dynamic UAV deployment also outperformed the static UAV deployment in terms of the required transmit power. More specifically, the dynamic UAV deployment required less total transmit power by a factor of about $1/2$ compared to the static UAV deployment.

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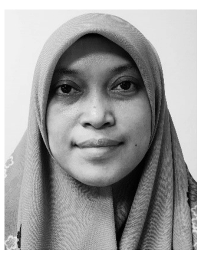

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