Enhancing UAV Deployment Efficiency: A PSO-Based Optimization Approach

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***Abstract*—This paper is about unmanned aerial vehicles (UAVs) as access points for delivering wireless services to users within an open, undeveloped area. The investigation focuses on three key aspects of deployment design within realistic Ground-linked communication channel models. These aspects include determining the minimum requirement of drones required for efficient service provision, identifying optimal deployment locations for these UAVs, and establishing the most effective allocation of transmit power for optimal performance. To independently address these design objectives, a novel approach is introduced, leveraging a particle swarm optimization (PSO)-based scheme with a balanced Signal-to-Interference-plus-Noise Ratio (SINR) transmit power allocation. Thorough simulations are conducted to validate the effectiveness of the proposed scheme, demonstrating its robust performance.**

I. INTRODUCTION

Unmanned aerial vehicles are getting a lot of attention as an innovative technology that can revolutionize wireless network topologies in the future. Because of their active mobility, they can act as dynamic relay nodes or access points that can adjust to changes in data flow in real-time. Regarding flight duration and energy resources, UAV deployment is subject to strict limits, unlike traditional base stations (BS). As a result, UAV networks have the possibility of much wider network coverage in addition to more flexibility in network building and planning. Specifically, drone networks is proposed as a way to restore emergency network services following natural disasters such as typhoons and earthquakes, where traditional communication infrastructure may be damaged. However, much further research is required to achieve the claimed benefits of UAVs in real-world applications. For assurance that the UAV is capable of high throughput and good coverage, placement optimization is crucial.

This paper explores a PSO-based approach aimed at collectively optimizing both the transmit power and locations of UAVs for a specified quantity of UAVs. The PSO technique is known for being simple to use for solving optimization problems [1]. Particles make up a swarm in the PSO algorithm, and each particle represents a possible solution inside a specific region [2]. The deployment scheme of UAVs is shown in Fig. 1. The two main updates that take place in the PSO algorithm are the particle velocities and their positions. The following formulas are used to calculate the updates in the PSO algorithm

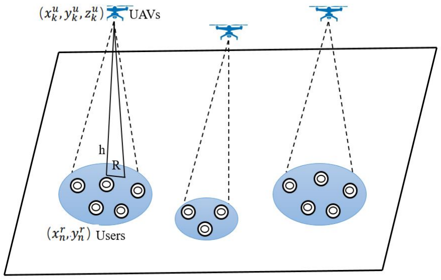

Fig. 1. UAV deployment senario

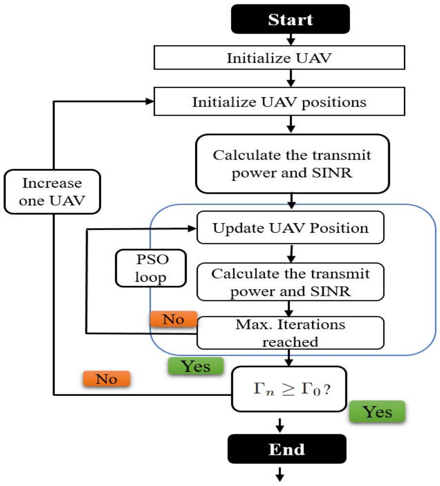

Fig. 2. Flowchart of PSO-based UAV deployment

$$V_i^n = \omega V_i^{n-1} + c_1 r_1 (P_{i,best} - X_i^{n-1}) + c_2 r_2 (G_{best} - X_i^{k-1}), \tag{1}$$

$$X_i^n = X_i^{n-1} + V_i^n, \tag{2}$$

In the equation 1, V_i^n represents the updated velocity of particles, V_i^{n-1} corresponds to the previous velocity, and ω in equation 1 serves as the inertial weight factor. Additionally, the terms c_1 and c_2 denote acceleration coefficients that enhance the inter-particle relationships, aiding each particle in converging towards the global optimal position [3]. The variables r_1 and r_2 are random variables within the range of $[0, 1]$, while $P_{i,best}$ indicates the individual best position discovered by each particle. Importantly, $Gbest$ does not refer to the individual particles; rather, it signifies the best position among all particles. Fig. 2 shows the flowchart of the PSO-based UAV deployment.

II. CONTRIBUTION

The use of UAVs, as access points to deliver services to users in underdeveloped, natural areas is the primary focus of this research. The research focuses on coverage values and does not consider the effects of small-scale fading in the following discussion. In decibels (dB), the route loss in ground linked communication between the k-th UAV and the n-th user is described as follows:

$$\mathcal{P}_{k,n}^{\mathrm{dB}} = \frac{A}{1 + je^{-d\left[\tan^{-1}\left(\frac{h_k^u}{R_{kn}}\right) - j\right]}} + 10\log\left((h_k^u)^2 + R_{k,n}^2\right) + B, \tag{3}$$

$$A = \eta_{los} - \eta_{nlos}, B = 20\log f + 20\log(4\pi/c) + \eta_{nlos}, \tag{4}$$

j, d, η_{los} and η_{nlos} are environment parameter. The assumption is that each user is attached to only one UAV. We also consider the interference from all the UAVs, safety distance, and UAV maximum transmit power. The minimum SINR requirement for all users is calculated as

$$\min_{n \in \mathcal{N}} \Gamma_n \geq \Gamma_0 \tag{5}$$

In our devised PSO-based approach, the parameter Γ_0 guides the updates to the UAV's location in every generation. If, even after reaching the maximum iteration limit, $\Gamma_0 > \Gamma_n$, the PSO-based scheme concludes that the existing number of UAVs is inadequate. After that, the proposed solution will be modified to add an additional UAV. If the requirements are not satisfied, the PSO-based system will be terminated. The PSO algorithm jointly optimized these UAVs locations and SINR requirement for users. The PSO method is used to reduce the accumulated path loss from one unmanned aerial vehicle to all users by optimizing the location of the UAV.

III. EXPERIMENTAL RESULTS

We conducted extensive simulations to verify the effectiveness of the proposed PSO-based system. In our simulated scenario, N users are distributed randomly and uniformly across an area of 300 300 square meters. When the number of users is small, specifically when N is below or equal to 10, a single UAV can cover all users, providing that each user achieves a well-balanced SINR higher than 0 dB. However when the number of user increase then one UAV cannot provide services to all users so the number of UAVs should be increased. When the number of user increases so we need to deploy more UAVS, In Fig. 3, we can see that one UAV is enough for 10 users, If the number of users are between 10 and 45, so we need to deploy three UAVs. Fig. 4 reveal for 60 and 70 number of user we need to deploy 4 and 5 UAVs respectively.

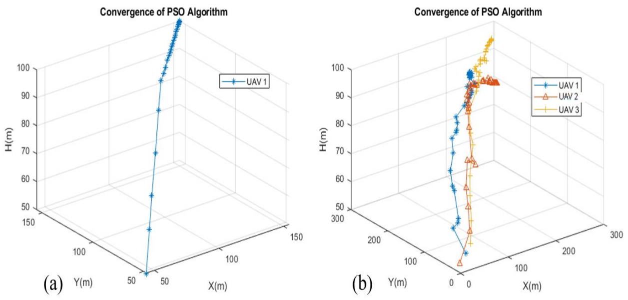

Fig. 3. UAVs location updated by PSO (a) User = 10, (b) User = 45

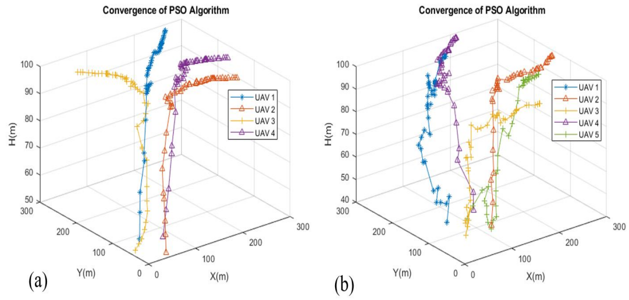

Fig. 4. UAVs location updated by PSO (a) User = 60, (b) User = 70

IV. ACKNOWLEDGEMENT

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V. CONCLUSION

This paper presents a particle swarm optimization based deployment approach for wireless networks with UAV assistance that must operate within interference limits. Two key deployment features are optimized by the scheme: figuring out the minimal number of UAVs and choosing the best deployment locations, in the best possible way to satisfy the required SINR. We use a SINR-balanced power allocation strategy to update the PSO algorithm every generation in order to obtain the best UAV positions. During each PSO iteration, a power allocation algorithm for SINR balancing computes the closed-form solutions for the optimum power distribution and then acknowledges the ideal SINR. This ability indicates that the provided PSO-based strategy converges to the most optimal UAV positions. The thorough simulation results validate the outstanding performance of the PSO-based system presented in this work.

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