Positioning Optimization of Base-Station Drone Arrays via Bioinspired Computing Techniques

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***Abstract*—This paper exposes a theoretical and simulational study of positioning optimization of base-station drones, in order to attend the greatest number of users with an acceptable signal strength. The objective is to provide a quick and precise optimization method to be employed in drone arrays providing Wi-Fi coverage. As such, three bioinspired computing optimization methods are discussed and evaluated for this scenario: the cuckoo search, the flower pollination algorithm and the bat algorithm. Simulations are done in a 3-drone system to validate and compare the bioinspired techniques.**

***Index Terms*—UAV, drones, coverage, bioinspired computation, optimization**

I. Introduction

One of the methods of wireless networking that are currently most studied, is the usage of unmanned aerial vehicles (UAVs or drones) [1]. Due to the high adaptability and free-form positioning of drones in 3D environments, they are often cited as the best devices for temporary or emergency wireless coverage, in cases such as equipment failure or natural disasters [2].

The employment of drones into wireless coverage problems is not novel, as surveys in the topic can attest [3], [4]. Generally, many studies have been done for positioning and/or trajectory tracing of drones, but few in the literature have studied the optimization of drone arrays for maximum user coverage. Most of the bioinspired optimization is applied to the UAV's path planning [5], [6], instead of optimal positioning to better attend users, which is the aim of this study.

Therefore, a theoretical and simulational analysis of UAV positioning optimization has been conducted in this paper via three bioinspired computing methods: the cuckoo search, the bat algorithm and the flower pollination algorithm. A performance and accuracy comparison is drawn between them, in order to inform which is the best for this kind of problem. The main objective of the algorithms employed is to maximize the number of users that shall be served by the UAV base-stations, given a certain area and number of drones.

The algorithms herein have been chosen for their lower computational cost and great precision in providing solutions to non-linear problems [7]–[9].

II. UAV Propagation Model

The path loss method utilized in this work aims at applications to outdoor and simple indoor propagation of wireless communications, valid for frequencies approximately around the Wi-Fi spectrum.

A. Path Loss Model

A path loss model that can be used for both Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) situations is surmounted in [10], with general equations (1), (2):

$$L_{(dB)} = 20\log\left(\frac{4\pi f d}{c}\right) + \zeta, \tag{1}$$

$$P_{LOS} = \frac{1}{Z}, Z = 1 + \alpha\exp(-\beta[\frac{180}{\pi}\theta] - \alpha), \tag{2}$$

in which f is the propagated frequency, ζ_{LOS} and ζ_{NLOS} are loss constants related to LOS and NLOS propagations, d is the distance from the UAV antenna to the terrestrial user's antenna $d = \sqrt{R^2 + h^2}$. Furthermore, $\theta = \tanh{(h/R)}$ is the elevation angle in radians and $P_{NLOS} = 1 - P_{LOS}$.

Hence, the average path loss experienced in propagation, the user received power and the disconnection threshold are given, respectively, in (3), (4):

$$L_{avg(R,h)} = P_{LOS} \times L_{LOS} + P_{NLOS} \times L_{NLOS}, \tag{3}$$

$$P_{r(dB)} = P_t + G_t + G_r - L_{avg}, \frac{P_r}{N} \geqslant \gamma \tag{4}$$

III. Simulations and Results

As an example of the validity of the optimization process, a 3-drone, 200-user system has been utilized. The total area of the problem is constituted of $4km^2$. Users are randomized under a normal distribution to the thereabouts of this area. The $\gamma = 30$ limit for base-station connection without cutoff is employed for the three UAVs, as it is, generally, recommended for Wi-Fi connections. The objective function Z for all optimization methods is denoted in (5). Ideally, this difference should be zero or near zero.

$$Z = |(U_{connected} - U_{total})| \tag{5}$$

The path loss model constants in all codes has been set to the details in Table 1. In total, 9 variables are utilized in the optimizations, representing the 3 spatial variables (x, y and height components) in relation to the users plane. The propagation constants have been chosen for a moderately urban environment [10]. All components x and y of the 3 UAVs are limited to -1000 to 1000 meters (in order to create the $4km^2$ search box) and all UAV heights are strictly between 100 to 200. For all optimization techniques, a limited number of 50 iterations and 25 solutions per iteration has been

TABLE I
VARIABLES AND CONSTANTS OF THE OPTIMIZATIONS

Parameters	**Values**
Transmitted Frequency	2.4 GHz
α	9.6
β	0.28
γ	30
ζ_{LOS}	1 dBm
ζ_{NLOS}	20 dBm
N (200 KHz bandwidth)	-120 dBm
G_t and G_r	0 dBm
Transmitted Power (all UAVs)	10 dBm

selected. Fitness values are given in Fig. 1. For Fig. 2, the black dots represent the users scattered around in a normal distribution and the red dots are the central positioning of the drones on the user plane. It presents the optimal positioning found by the Flower Pollination Algorithm, given that it has displayed the best convergence of all three techniques. The error (number of disconnected users) and running time data for each optimization method is described in Table 2.

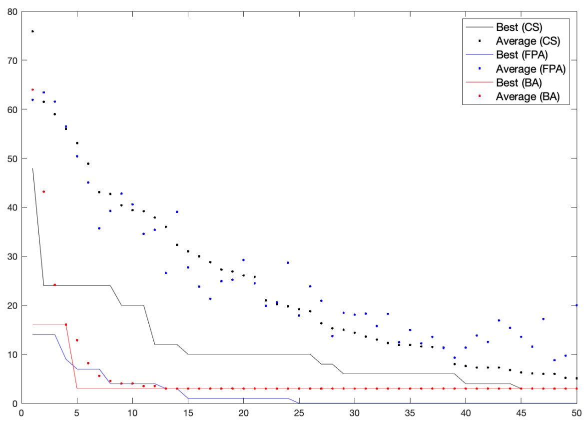

Fig. 1. Fitness values for the three algorithms

TABLE II
OPTIMIZATION RESULTS

Method	**Error**	**Running time (in seconds)**
Cuckoo Search	3	8.079
Flower Pollination	0	12.232
Bat Algorithm	3	6.798

IV. CONCLUSION

A discourse on UAV base-stations with bioinspired computing optimization has been realized in this paper. It is safe to denote that the Flower Pollination technique demonstrates faster convergence in its fitness graph, yielding more trusting results. However, as the quickest solution, the Bat Algorithm has the best time and displayed a small error of only 3 disconnected users out of 200 - which are still satisfactory results

Fig. 2. Flower pollination algorithm's optimal positioning

in regards to cost/benefit. A finer tuning of the parameters inserted would, perhaps, yield better results with even less time consumption.

For further studies, an expansion with variables to control UAV-to-UAV interference and/or power efficiency issues would be of great interest to enhance what there already is in the literature.

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