A Social Spider Optimisation Algorithm for 3D Unmanned Aerial Base Stations Placement

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***Abstract*—In recent years, the use of drones as aerial base stations (ABS) has attracted the attention of both scientific and industrial communities as a promising solution to enhance the network coverage. However, their deployment brings out many challenges and restrictions. In this work, we model a realistic, constrained scenario where unmanned aerial vehicles (UAVs) are used as ABSs along with traditional ground base stations (GBSs) to extend their coverage. We propose a scalable and efficient social spider optimization (SSO) algorithm that determines the placement of UAVs and their association with both user equipments (UEs) and GBSs. Extensive computational experiments were conducted to investigate the effect of the different SSO metaheuristic parameters and tune them to the best values. The efficiency of the proposed solution is then evaluated by comparing its results to two other schemes. Simulation results show that the proposed approach overcomes the two other strategies and presents an average gain of 18% and 31% compared to the them.**

***Index Terms*—drones, UAV, social spider optimisation, aerial base stations, MINLP.**

I. Introduction

The market of civilian and commercial drones (also known as unmanned aerial vehicles or UAVs) has experienced significant growth recently, and is expected to support the definition of a growing number of ambitious use cases in the 5G vertical domains [1]. Using UAVs in wireless cellular networks as aerial base stations (ABS) to assist the ground base stations (GBSs) and provide coverage to unserved distant users is a high-potential solution for the new generations of networks, that brings out many challenges including: the optimal 3D placement of ABSs, coverage optimization, resource allocation, cell association and interference management [2]. Unlike ground BS, that has a strong reliable wired/wireless backhaul connection, Untethered aerial base stations can only have a limited wireless backhaul link. This latter is highly susceptible to interference originating from a wide variety of sources, such as adverse weather conditions, other small cells, and macrocells as well [3]. Wireless backhaul restraints the number of users that it can serve, and is affected by the UAV's position regarding to the GBS that provides it. In this paper, we tackle the challenging problem of positioning a swarm of ABSs, in order to extend the cellular network coverage. The problem was addressed in a set of existing papers [4]- [5]. Yet, to the best of our knowledge, the existing works ignore the restraint backhaul constraint and the impact of the ABS's position -regarding to the GBS- on the backhaul capacity. They either consider unlimited backhaul capacity or a fixed limited capacity. The contributions of this paper are:

- We present and model a realistic, constrained scenario where UAVs are used as ABSs along with traditional ground base stations to extend their coverage,
- Unlike most existing works that simplify scenario's assumptions, we consider the backhaul constraint, in addition to interference between ABSs and GBSs and use reliable 3GPP models to characterize channels,
- We propose a scalable and efficient metaheuristic Social Spider (SSO) Algorithm that determines UAV's placement and their association with both UEs and GBSs,
- We conduct extensive computational experiments to tune the parameters of the SSO and assess its efficiency.

The remainder of this paper is structured as follows: Section II provides a brief overview of the literature related to the use of UAVs as ABS. The optimization problem is presented in Section III and solved using a Social Spider Optimisation algorithm in Section IV. In Section V, the numerical simulation results are provided and discussed. Finally, Section VI draws the final conclusions.

II. Related Work

The optimal placement of ABS in cellular networks have been the subject of many papers that investigated it under quality-of-service constraints, in order to maximize the number of covered users. Two main categories can be distinguished:

A. Single ABS placement

In [6] and [7], the 3D placement of a single ABS, in order to maximize the number of covered users is studied. The problem in [6] is formulated as a quadratically-constrained mixed integer non-linear optimization problem, and a numerical solution is proposed to solve it. While, in [7], it is modeled as a circle placement and smallest enclosing circle problem under the constraint of minimizing transmit power. In [8], the optimal positioning of an ABS acting as a relay between a GBS and a fixed position user in is investigated. The authors in [9] study the efficiency of integration ABS into cellular networks as an alternative to ultra-dense small cell deployment. They deploy a single ABS to assist the ground base station network and serve a group of moving users.

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B. Multiple ABS placement

The authors in [10] considered the problem of covering a ground area using two ABSs, and investigated the impact of the altitude and the distance between ABSs on coverage. In [5], both drone base stations and drone users are considered. A truncated octahedron shapes based method is proposed for the 3-D placement of drone BSs and the optimal cell association is then defined using optimal transport theory with the objective of minimizing drone users' latency. In [11], the authors propose a framework that uses a swarm of ABSs to assist a ground cellular network. It places the ABSs according to a network planning approach based on stochastic geometry.

However, none of these works studied the 3D placement of ABSs to maximize coverage with the constraint of backhaul link between ABSs and GBSs except [12] and [13]. In [12], an algorithm for the 3D placement of ABS and their users association is proposed. It considers wireless backhaul constraint and its allocation management. Nonetheless, it doesn't consider the interfering signals between ABSs, GBSs, and users. Authors in [13] consider the 3D placement of ABSs to maximize coverage and the maximum rate of users under a predefined limited backhaul rate and bandwidth. To the best of authors' knowledge, this article is unique on its definition of the 3D unmanned ABSs placement problem; as it considers the backhaul constraint and the impact of the ABS's position on its capacity and the number of UEs that can be served.

III. Optimization Problem Modeling

We consider a wireless communication system, where $K \geq 1$ GBSs are deployed to cover and provide access to a set of terrestrial mobile users, and a limited group of $M \geq 1$ UAVs acting as ABSs to extend coverage and provide access to the subset of $N \geq 1$ remaining uncovered single-antenna UEs. Each ABS must be connected to a GBS by a sufficiently high speed backhaul, through which information exchange and traffic offload with negligible delays is possible. The GBS, UE, and ABS sets are denoted as **K**, **N** and **M**, respectively. Their positions are defined as $U = \{u_1, u_2, u_3, ...u_k\}$, $V = \{v_1, v_2, v_3, ...v_m\}$ and $W = \{w_1, w_2, w_3, ...w_n\}$, respectively.

We consider a downlink scenario in which each ABS, schedules transmission over contiguous Resource Blocks (RB), each consisting of a block of orthogonal frequency-division multiplexing sub-carriers. The transmitting power of ABSs on each RB is assumed to be constant.

We adopt reliable models for the characterization of the wireless channels between GBSs, ABSs and UE. They were tested and approved by the 3rd generation partnership project (3GPP), or by scientific papers. Accordingly, for communication between:

- An ABS and a UE, we use the channel model from [14],
- An ABS and a GBS, we use the channel model from the 3GPP technical specifications [15],
- A GBS and a UE, we use the channel model from the 3GPP technical specifications [16],
- Two ABSs, we use the channel model proposed in [17]

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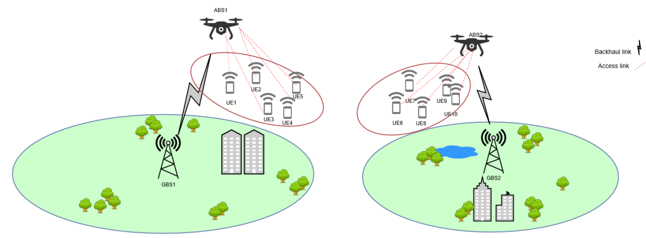

Fig. 1: System model

A. Problem Formulation

In this section we formulate the problem of finding the 3D coordinates of a set of ABSs in order to extend the cellular network served and maximize the number of covered UEs.

We define the user, and backhaul association indicators $I_{n,m}$, $J_{l,k}$, respectively, as:

$$I_{n,m} = \begin{cases} 1, & \text{if user } n \text{ is served by ABS } m \\ 0, & \text{otherwise} \end{cases}$$

$$J_{l,k} = \begin{cases} 1, & \text{if ABS } l \text{ is getting backhaul from GBS } k \\ 0, & \text{otherwise} \end{cases}$$

Note that a UE n can be served by an ABS m if it experiences SINR equal to or higher than the required threshold. its reachable throughput $R_{m,n}$ can be calculated from its $SINR$, using Shannon expression [18]. We denote the capacity of the backhaul link that an ABS m receives from a GBS k as $R_{k,m}$.

The total number of served UEs can be calculated as:

$$S = \sum_{n \in N} \sum_{m \in M} I_{n,m}$$

The required backhaul capacity for ABS m is expressed as:

$$Z_m = \sum_{n \in N} I_{n,m} \cdot R_{m,n} \tag{1}$$

The objective is to find the optimal 3D positioning U_{best} of the ABSs & the joint association of UEs with their serving ABSs I and the ABSs association with the GBSs providing backhaul link J, in order to maximize the coverage, while respecting the backhaul constraint. This can be formulated as:

$$\max_{U,I,J} \sum_{n \in N} \sum_{m \in M} I_{n,m} \tag{2}$$

subject to:

$$Z_m \leq \sum_{k \in K} J_{m,k} \cdot R_{k,m} \quad \forall m \in M \tag{3}$$

$$\sum_{m \in M} I_{n,m} \leq 1 \quad \forall n \in N \tag{4}$$

$$\sum_{k \in K} J_{m,k} \leq 1 \quad \forall m \in M \tag{5}$$

where (3) ensures that the access provided by an ABS doesn't exceed its backhaul capacity, (4) denotes that a UE can't be served by more than one ABS, while (5) denotes that an ABS can't get backhaul from more than one GBS.

Due to binary variables I, J, and continuous variables U, the aforementioned ABSs positioning, and joint user & backhaul association problem is considered as a mixed-integer nonlinear programming (MINLP) problem. MINLP problems have the difficulties of both of their sub-classes, i.e., the combinatorial nature of mixed-integer programming (MIP) and the difficulty in solving nonlinear programming (NLP). Since both MIP and NLP are NP-hard, our ABSs placement problem is considered as NP-hard and can't be solved in a polynomial time. We propose -in the next section- to adapt the metaheuristic method, Social Spider Optimisation (SSO) [19], to our problem. This choice is justified by the fact that the SSO has demonstrated its efficiency and scalability on many NP-hard optimization problems [20].

IV. SSO Algorithm for 3D ABS Placement

SSO is a recent swarm algorithm, based on an iterative process. Basically, a population of initial solutions is generated and classified. Each solution is represented by a male or female search agent (spider). At each iteration, the set of female and male spiders move according to their cooperative operators. The information about encountered solutions is exchanged by emitting vibrations over the communal web. Nearby male and female members mate, thereby forming new offspring solutions. The population is then updated and the resulting broods replace the worst members. The process finishes when a fixed number of iterations, without improvement of the population is reached. The best solution is then returned. The main steps of our adapted SSO are described in the following.

A. Population initialisation

Each solution s represented by a spider i is the 3D coordinates of the M ABSs, and has a fitness value $J(s_i)$ regarding to the objective function. Each member of the initial population is randomly generated by placing the M ABSs over the search space. A weight w_i is assigned to each spider i, to indicate the quality of its solution: $w_i = \frac{J(s_i) - worst_s}{best_s - worst_s}$

Where $best_s$ and $worst_s$ represent the best and the worst fitness value of the population, respectively.

B. Spider's evaluation

To compute the fitness of a spider and evaluate the quality of its solution, the joint association of ABS to the GBS providing backhaul link and UEs to their serving ABSs must be performed. Here, we propose a heuristic algorithm inspired by [21], that assigns each UE to its serving ABS.

We first associate each ABS i to the GBS providing the highest SINR, to maximize its backhaul capacity Z_i. We then associate each UE j to the ABS providing the highest SINR if it has a sufficient backhaul capacity as in Algorithm 1.

C. Information exchange and moving spiders

The coordination between the members of the population is provided by the important messages that individuals exchange.

Algorithm 1 UEs association algorithm

Input: The positions of GBSs, ABSs, and UEs
Output: L_i list of UEs served by each ABS i
Compute the SINR between each ABS and GBS.
Associate each ABS i to the GBS with the highest SINR and compute its backhaul capacity Z_i.
Compute SINR between each UE and ABS.
for each UE j **do**
  Sort the list of possibly serving ABS M_j according to their experienced $SINR$, in descending order.
  for $k = 1$ to $M_j.size$ **do**
    $cand \leftarrow M_j[k]$; Compute the required rate $R_{j,cand}$
    if $R_{j,cand} \leq Z_{cand}$ **then**
      $L_{cand} \leftarrow L_{cand} + j$; $Z_{cand} \leftarrow Z_{cand} - SINR_{j,cand}$
      break;
return L

These messages are encoded as small vibrations and transmitted over the communal web. Practically, the vibrations that the spider i perceives from the spider j are expressed as follows: $Vib_{i,j} = w_j \cdot e^{-d_{i,j}^2}$ where $d_{i,j}$ is the Euclidean distance between the individuals i and j. Based on these messages, social spiders move and change their positions:

1) Female operator: Each female i demonstrates an attraction or repulsion behavior. It is modeled as the position change of i and depends on a combination of three factors:

- The local best member s_c: that emits the vibration $Vibc_i$.
- The global best member s_b: emitting the vibration $Vibb_i$.
- The random factor.

The choice of attraction or repulsion is a stochastic decision. Thus, the female's changing position is implemented as:

$$f_i^{k+1} = \begin{cases} f_i^k + \alpha \cdot Vibc_i \cdot (s_c - f_i^k) + \beta \cdot Vibb_i \cdot (s_b - f_i^k) \\ +\gamma \cdot (rand - 1/2) \text{ with probability } p_f \\ f_i^k - \alpha \cdot Vibc_i \cdot (s_c - f_i^k) - \beta \cdot Vibb_i \cdot (s_b - f_i^k) \\ -\gamma \cdot (rand - 1/2) \text{ with probability } 1 - p_f \end{cases}$$

2) Male operator: based on their weight, we distinguish:

- Dominant males: show an attraction to the closest female s_f, emitting the vibration $Vibf_i$ to perform mating.
- Non dominant males: they are attracted to the weighted mean of the the male individuals, so as to benefit from their underemployed resources.

Thus, the male's changing position is implemented as:

$$m_i^{k+1} = \begin{cases} m_i^k + \alpha \cdot Vibf_i \cdot (s_f - m_i^k) + \gamma \cdot (rand - 1/2) \\ \text{ for dominant males} \\ m_i^k + \alpha \cdot (\frac{\sum_{h=1}^{N_m} m_h^k \cdot w_{N_f+h}}{\sum_{h=1}^{N_m} w_{N_f+h}}) \text{ for non-dominant males} \end{cases}$$

D. Mating operator

Mating operation is carried out by a dominant male m_m, with a set E^f of the closest females, located within it's influence radius r, in order to produce a new off-spring.

TABLE I: Basic Parameters

Parameter	Value
Carrier frequency	2GHz
ABSs/GBSs bandwidth	20/20 MHz
Tx power of ABS	36dBm
Tx power of GBS	41dBm
SINR threshold	-7dB

TABLE II: Scenarios' Specifications

scenario	area size	GBSs	UEs	ABS
small	2km x 2km	1	100	10
medium	4km x 4km	2	200	10
large	5km x 5km	3	400	15

The resulting brood's solution is a combination of its parents $E^{mat} = E^f \cap m_m$ configurations. The effect of each parent on the new off-spring depends on its weight, and is determined by the roulette wheel, i.e. the probability p_i of the influence of the parent $i \in E^{mat}$ is calculated as: $p_i = \frac{w_i}{\sum_{j \in E^{mat}} w_j}$

Algorithm 2 SSO algorithm

Input: pop_{size}, $iter_{max}$
Output: S_{best} Best spider with best solution
generate the initial population of spiders.
Evaluate the fitness of each spider S_i
$iter \leftarrow 0$
while $iter <= iter_{max}$ **do**
    $iter \leftarrow iter++$
    Compute the weight of each spider S_i.
    Update each female/male position.
    for each spider S_i **do**
        evaluate fitness $J(s_i)$
        if $J(s_i) > J_{max}$ **then**
            $J_{max} \leftarrow J(s_i)$; $S_{best} = S_i$; $iter \leftarrow 0$
    Perform Mating.
    Evaluate the new off-spring S_0
    if $J(s_0) > J_{min}$ **then**
        Replace the worst spider by the new offspring
return S_{best}

V. Simulation Scenarios and Performance Evaluation

In the following, we present the computational experiments that were carried out in order to tune our SSO and evaluate its performance. Our algorithm was coded using Matlab. All the simulations were conducted on an Intel Xeon E5-2620 (16 Cores), 2.60GHz CPU, with 32GB memory (RAM).

To assess the scalability of the proposed algorithm, three different scenarios with different area sizes, UEs, ABSs and GBSs numbers are generated as illustrated in Table II. The basic transmission parameters are summarized in Table I.

A. SSO Parameters

The proposed SSO has two major parameters:

- pop_{size}, the number of search agents (spiders);
- $iter_{max}$, or the stopping condition: the number of iterations without improvement of the global best solution.

To find the right values for pop_{Size} and $iter_{max}$, we ran the algorithm on the medium scenario, while varying the value of pop_{Size} between 5 and 20, and $iter_{max}$ between 5 and 25. The experiment was repeated 15 times, each time with a different random seed. We then computed the percentage deviation between the best achieved solution SSO and the best solution achieved over all the runs J_{max} as: $GAP = (\frac{J_{max} - SSO}{J_{max}}) \times 100$. The collected results of are summarized in Fig. 2, while Fig. 3 shows the average sruntime.

For all compared population sizes in Fig. 2, the average deviation (GAP) is decreasing and the solution quality is improving with the increase of $iter_{max}$. In fact, as the $iter_{max}$ increases, SSO keeps exploring new search areas and candidate solutions that improve the best solution's quality. As can be seen, the values $iter_{max}$ = 25 and $iter_{max}$ = 20 lead to the best solutions quality with GAPs of 0% and 1%, respectively.

The experiments show that increasing the size of the population significantly improves the GAP. SSO could not find good solutions using small population size – 5 or 10 spiders. It needs at least 15 spiders to achieve better solutions. The further increase in the size of population does not lead to significantly better results (less than 2%). It leads only to an increase in computational time without significantly improving the value of the objective function as can be seen in Fig.3 . The CPU time needed to find a good solution increases with increasing memory size. This latter must be large enough for the solutions it contains to be diverse, but small enough for the problem to be solved in a reasonable time.

Finally, the parameters $iter_{max}$ and pop_{size} control the computational time of the algorithm, and in order to achieve a good compromise between the quality of the solution and the execution time, we exclude $iter_{max} = 25$ because of the higher computation times and we opted in the following to set $pop_{size} = 15$ and $iter_{max} = 20$.

B. Performance evaluation

To the best of our knowledge, our SSO algorithm is the first algorithm to consider ABS's placement according to backhaul capacity constraints in interfering conditions. Thus, in order to evaluate the performance of our proposed heuristic approach, we carry out a comparison between its results and those of:

- The random search (RS) [22]: tries a number of randomly chosen points in the search space, and holds the candidate point with the best fitness value as the optimum solution,
- A uniform deployment (UD) of the ABSs.

The results of RS, UD and the SSO were obtained with 15 runs of each algorithm on each scenario.

Figure 4 depicts the mean values and 95% Confidence Interval (CI) of the ratio of served UEs of our SSO compared with those obtained with the RS and UD strategies, for the three scenarios. Despite the fact that we provide the same number of ABSs, SSO clearly outperforms the RS and UD strategies. It presents an average gain of 18% and 31% over

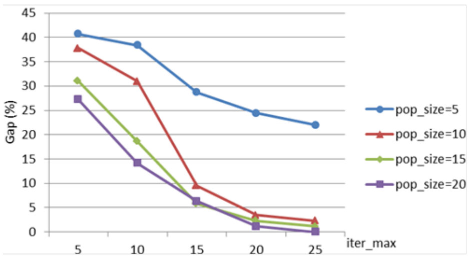

Fig. 2: Effects of pop_{size} and $iter_{max}$ on solution quality

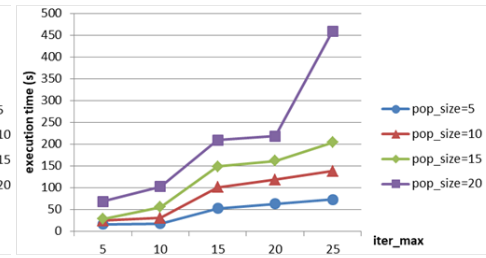

Fig. 3: Effects of pop_{size} and $iter_{max}$ on the execution time

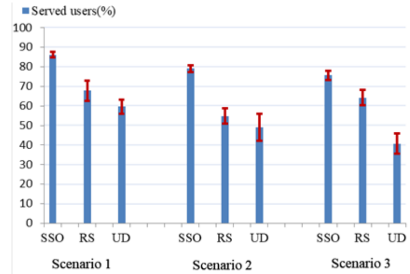

Fig. 4: Results comparison

the RS and UD, respectively. In fact, the UD places the ABSs uniformly over the search space, without considering the UEs distributions, which leads to low coverage rates that globally doesn't exceed 50%. The RS tends to move randomly over the search space in order to explore it, which provides a total coverage rate of nearly 62%, while the SSO uses different search agents (spiders) to explore the candidate solution's domain efficiently, leading to better performance and larger average coverage rates of almost 81%.

VI. Conclusion

In this paper, we have proposed a novel algorithm to solve efficiently the 3D placement of ABSs and joint user & backhaul association problem. The performance evaluation shows that the proposed approach significantly improves the coverage rate of ABSs by serving an average of 81% of the total number of users. In future works, we aim to extend our solution to allow the consideration of multi-hop backhaul links, where communication and coordination between the swarm of ABSs is crucial.

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