COMPARATIVE STUDY OF META-HEURISTIC ALGORITHMS IN THE UAV-BS POSITIONING SOLUTION

ESTUDO COMPARATIVO DE ALGORITMOS META-HEURÍSTICOS NA SOLUÇÃO DE POSICIONAMENTO UAV-BS

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ABSTRACT
Unmanned Aerial Vehicles as Base Stations (UAV- BS) are capable of reestablishing user connectivity in natural disaster scenarios. Optimizing the positioning of UAV-BS presents significant challenges, including identifying the most suitable metaheuristic for implementation. This study proposes the eval- uation of five metaheuristic algorithms (ABC, ACO, GA, PSO, and TLBO) to optimize UAV-BS positioning considering user coverage, signal quality, and computational cost. Comparative models were used to evaluate the performance of the algorithms, indicating superior advantages of TLBO and PSO.

Keywords: UAV. Base Station. Metaheuristic Algorithms.

RESUMO
Veículos Aéreos Não Tripulados como Estações Base (UAV-BS) são capazes de restabelecer a conectividade do usuário em cenários de desastres naturais. Otimizar o posicionamento de UAV-BS apresenta desafios significativos, incluindo a identificação da metaheurística mais adequada para implementação. Este estudo propõe a avaliação de cinco algoritmos metaheurísticos (ABC, ACO, GA, PSO e TLBO) para otimizar o posicionamento de UAV-BS, considerando a cobertura do usuário, a qualidade do sinal e o

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custo computacional. Modelos comparativos foram utilizados para avaliar o desempenho dos algoritmos, indicando vantagens superiores de TLBO e PSO.

Palavras-chave: VANT. Estação Base. Algoritmos Metaheurísticos.

RESUMEN

Los vehículos aéreos no tripulados como estaciones base (UAV-BS) son capaces de restablecer la conectividad de los usuarios en escenarios de desastres naturales. Optimizar el posicionamiento de los UAV-BS presenta desafíos significativos, incluyendo la identificación de la metaheurística más adecuada para su implementación. Este estudio propone la evaluación de cinco algoritmos metaheurísticos (ABC, ACO, GA, PSO y TLBO) para optimizar el posicionamiento de los UAV-BS, considerando la cobertura del usuario, la calidad de la señal y el costo computacional. Se utilizaron modelos comparativos para evaluar el rendimiento de los algoritmos, indicando ventajas superiores de TLBO y PSO.

Palabras clave: UAV. Estación base. Algoritmos Metaheurísticos.

1 INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have emerged as a promising solution due to their flexibility and ability to rapid deployment, acting as Base Stations to re-establish connectivity in natural disaster scenarios. Optimizing UAV-BS positioning, however, presents significant challenges. It is necessary to dynamically adapt to changing landscapes, user density, and quality of service (QoS) requirements, making a relevant contribution to modern and future mobile networks.

Meta-heuristic algorithms are proposed in the literature to address UAV-BS positioning, including ABC Bee Colony Algorithm Optimization, ACO Ant Colony Optimization Algorithm, AG Gene Algorithm, Particle Swarm Optmization) and Teaching-Learning Based Optimization (TLBO).

Despite significant advances in the use of metaheuristic algorithms to optimize the positioning of the UAV-BS, there are still gaps in the literature regarding the choice of the most appropriate metaheurestic. This research aims to fill this gap by comparing the performance of different metaheuristics to identify the most efficient.

In this sense, this study proposes to implement and evaluate optimization methods for UAV-BS positioning. Specifically, it aims to: (1) Compare and evaluate different meta-heuristic algorithms (AG, PSO, ACO, ABC and TLBO) to determine the optimal or suboptimal position of UAV-BS; (2) Analyze the correlation between different performance metrics, such as number of connected users, throughput, and execution time; (3) Identify the most efficient meta-heuristic in terms of quality of service and computational cost, providing practical recommendations for implementation.

The main contribution of this article is to provide a comparative analysis of the performance of five meta-heuristics in optimizing UAV-BS positioning. This study broadens the theoretical knowledge about optimization algorithms, highlighting the importance of selecting the appropriate algorithm to maximize user coverage and signal quality, minimizing response time and computational cost.

The rest of the document is organized as follows: Section II presents the related works. Section III describes the methodology used. Section IV discusses the results. Finally, Section V concludes the work.

2 RELATED WORKS

The effective positioning of UAVs to maximize user coverage is a complex challenge addressed by several studies. In [1], a robust algorithm for the placement of UAVs in smart cities was proposed, highlighting the effectiveness of meta-heuristic approaches. Already, [2] introduced a meta-heuristic-based algorithm to maximize coverage with the minimum number of UAVs.

In [3] the authors demonstrated the relevance of the use of the PSO by proposing an algorithm to optimize the coverage of base stations in UAVs, while [4] focused on maximizing user coverage through the joint optimization of UAV positioning and the path loss compensation factor.

For the selection of UAV-BS sites, [5] they proposed a method based on the spiral algorithm, integrating ACO for optimal planning. Additionally, [6] demonstrated the applicability of ACO in continuous domains for optimization problems.

In [7], the use of ACO to optimize the path in mobile edge computing was presented, while [8] they used the ACO to minimize the path cost of UAVs in Wireless Sensor Networks (WSN).

The effectiveness of the genetic algorithms was highlighted in [9], which optimized parameters for a direct adaptive controller in UAV-BS attitude control. In [10], a method was presented to maximize the satisfaction of the of UAVs with ABC, considering constraints such as collision prevention and formation stability.

TLBO has been applied in the positioning of UAVs in [14], optimizing emergency tasks of multiple UAVs, improving the effectiveness of convergence, and ensuring the efficient completion of missions.

3 METHODOLOGY

This section provides a detailed description of the simulated environment in which the metaheurstic solutions were evaluated, as well as the metrics used and the form of collection.

A. Simulation Environment

The research is conducted in a simulation environment that models signal propagation and interference in an area of 1000m x 1000m, considering a frequency of 2.4GHz. For the construction of the scenario, Python was used, in the version

3.2.12. For data analysis and visualization, the most up-to-date versions of the NumPy (1.26.0) and Matplotlib (3.9) libraries were used.

In the constructed setting, users are randomly distributed. However, for a comparative analysis between the different types of meta-heuristic algorithms, a seed is assigned to the randomness of the position of the users, using the Random module of Python, with the objective of creating identical search scenarios for all algorithms.

B. Placement planning

When planning the positioning of UAV-BS, electromagnetic propagation presents several challenges, which should consider the communication between UAV-BS and terrestrial users, taking into account some concepts and factors that affect this communication.

To calculate the distance from users to UAV-BS, the Euclidean distance equation is used in a widely understood two-dimensional plane, which calculates the distance between two points (x, y) and (xi, yi) [15].

C. Propagation Model

The Air-To-Ground (A2G) path loss model [16] was used, which takes into account LLoS as the line of sight (LoS) and ηLoS as the line of sight (NLoS) between the UAV-BS and the ground user. Where LoS and S are losses of propagation in the free space and depend on the environment, as [17]. The model is expressed as:

$$PLLoS\,(dB) = 20\log10\,\frac{4\pi fcdij}{c} + \eta_{Them} \quad (1)$$

Where:

fc is a variable representing the carrier frequency, dij and distance in meters, and c is a constant representing the speed of light [16].

D. Signal-Interference Ratio plus Noise

We assume that the Signal-to-Interference-Plus-Noise Ratio (SINR) is used to provide theoretical upper limits for the channel capability in wireless communication systems. The SINR represents the scene where the background noise and the intensity of interference from other simultaneous transmissions are also considered.

In this experiment we consider that, during the period of time in which the UAV-BS is transmitting data to terrestrial users, the UAV-BS maintains a constant altitude and speed. We assume that it has fewer obstacles for the UAV-BS to operate efficiently at lower heights, 50 meters, taking better advantage of direct visibility [18]. We estimate that each node transmits with the same power, to allow direct comparisons between the different algorithms, which is the focus of the work. The formula for the SINR calculation [19].

$$\mathrm{SINR} = \frac{P}{I + N} \qquad (2)$$

Where:

- P´ is the power of the signal of interest.
- I´ is the interference power of other signals in the network.
- It is not the power of noise.

E. Shannon's Calculation

To calculate the transmission rate or throughput of the network, it indicates the rate of bits transmitted in a range time, and Shannon's formula [20] was used. The rate of achievable user and expressed as:

$$C = B \log_2 \left(1 + \frac{Puq}{LN0B}\right) \qquad (3)$$

Where: B is the bandwidth allocated per user, Pu is the power transmitted by the UAV-BS, G is the directional antenna gain, L represents the path loss defined in (1) and N0 and´ the spectral power density of the noise [21].

F. Benchmarking of Algorithms

For the evaluation scenario, a computer equipped with an Intel(R) Core(TM) i5-8350U CPU 1.70GHz - 1.90GHz, with 8GB of RAM memory and an Intel(R) UHD Graphics 620 video card was used.

Variations of 2 to 6 UAV-BS were tested in the experiments, running each algorithm 30 times for each configuration. This approach allowed the evaluation of the convergence and resilience capacity of the algorithms under different conditions.

1) Static Significance Test: To evaluate the performance of different algorithms, the static significance test was used, specifically the Analysis of Variance [22] which aims to verify the existence of significant differences between the algorithms for

each metric evaluated: number of Connected Users (CU), SINR, Leakage and Execution Time (TE).

2) Superiority calculation: The formula used to calculate the percentage superiority of one meta-heurstic over the other is given by:

$$S\ (\%) = \frac{\vartheta - \iota}{\iota} X100 \qquad (4)$$

G. Metaheurstic Algorithms

In this study, we searched for algorithms inspired by different natural phenomena (bees, ants, gene evolution, particle social behavior, and teaching-learning processes), ensuring a diversity of strategies and solution mechanisms that broadly cover the spectrum of possible solutions. At the end of each meta-heuristic, it is sought to optimize the positioning of the UAV-BS in order to maximize the coverage and signal quality for users.

The meta-heuristic algorithms used were: The ABC that simulates the foraging behavior of bees to find optimal solutions, having a simple structure, with few parameters for adjustment, which facilitates its implementation and reduces the computational load [23]. The ACO that is based on the path-finding behavior of ants that use the pheromone for path planning optimization, excellent for solving problems combinations and has adaptability to changes in the environment.

This is crucial for scenarios where network topology and demand can vary [24]. The AG that uses concepts of natural and genetic selection to evolve solutions over several generations, acting with flexibility and robustness in exploring [22] which aims to verify the existence of significant differences between the algorithms for each metric evaluated: number of Connected Users (CU), SINR, Leakage and Execution Time (TE).

Search spaces, being effective in avoiding local minimums through genetic operations [25]. The PSO draws inspiration from the social behavior of swarms such as birds and fish to find optimal solutions, exploring the search space globally, using a population of particles that adjust their positions based on their own experiences and those of their neighbors [26]. The TLBO is an algorithm based on the teaching and learning process in the classroom where the "students" (solutions) learn from the "teacher" (the best solution) and from each other, balancing the exploration without the need for many adjustable parameters, which facilitates its implementation and use [27].

Table I presents the parameters for the application of algorithms to solve the problem. The general parameters of the scene are presented in the Table II.

H. Fitness Function

The fitness function of this problem evaluates how well the access points (UAV-BS) are distributed to maximize the number of connected users with a desired SINR. It is defined as:

Table 1

Parameters of meta-heuristic algorithms

Algorithm	Parameter	Value
ABC	Maximum iterations	100
	Bound	200
ACO	Evaporation rate	0.1
	Pheromones (α)	1
	Heuristic information (β)	1
	Pheromon deposit	1
	Initial Pheromone	0.5
	Maximum iterations	100
AG	Number of generations	250
	Population size	250
	Change rate	0.1
PSO	Number of particles	200
	Maximum iterations	10
	Weight of the Industry	0.5
	Cognitive Weight	0.5
	Social Weight	0.8
TLBO	Maximum iterations	400
	Learning Rate	1.0

Table 2

Table of parameters of the simulation

Parameter	Value
Number of Users	100
Number of UAV-BS Points	2 - 6
Search space size	1000m x 1000m
Signal Power	-80dBm
Noise Power	38dBm
Frequency	2.4GHz
SINR Desired	25dB
UAV-BS Height	50m
Receiving antenna height	1.2m

In the analysis of the data, the performance of the different optimization algorithms is represented in Figure 1, demonstrating the performance regarding the connection of users to the different amounts of UAV-BS.

$$\text{Fitness} = \sum_{i} \begin{cases} 1 & \text{SE SINRi} \geq \text{SINR Objective} \\ 0 & \text{otherwise} \end{cases} \qquad (5)$$

Where: *i* is the user evaluated.

This wording accounts for the number of users whose assessed user SINR is higher than the objective SINR.

I. Data Collection Procedure

1. Initiation of random positions of UAV-BS and users in the search space;
2. SINR calculation for each UAV-BS/user pair;
3. Execution of meta-heuristic algorithms to optimize the positions of UAV-BS;
4. Record of the optimal or suboptimal positions found, percentage of connected users, SINR reached, throughput (Mbps) and computational cost (algorithm execution time).

4 FINDINGS

Table III presents the results of the F and P-value statutory tests established in the static significance test: The static significance tests showed that the P-value, equal to or close to zero, confirm the hypothesis that the choice of the algorithm directly impacts the results, ecause the closer it is to zero, the higher the significance statics of the evaluation.

In the analysis of the data, the performance of the different optimization algorithms is represented in Figure 1, demonstrating the performance regarding the connection of users to the different amounts of UAV-BS.

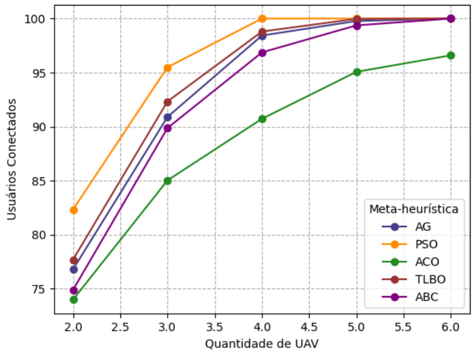
Table 3

Results of the static significance

Mythology	Static F	P-value
Connected Users	14,41	2.46 x 10−11
SINR	1585,89	0,0
Leakage	159,11	2.21 x 10−98
Execution time	85,13	1.49 x 10−59

Figure 1

Performance of Algorithms for UAV-BS Connected Users



It was revealed that the number of connected users, obtained through fitness metrics, varies significantly between algorithms, with TLBO and PSO often connecting more users compared to the other algorithms. It is noticed that the PSO algorithm presents better results in the search for optimal solutions when it comes to connected users, because with 4 UAV-BS it achieves the maximum connection of 100% of users and remains stable. The AG, ABC and TLBO algorithms show a consistent improvement in the number of connected users as the number of UAV-BS increases, but they reach the total connection with only 6 UAV-BS, although with 5 UAV-BS they already indicate a high level of efficiency. However, the ACO algorithm does not converge very well in user coverage, presenting the lowest performance among the algorithms analyzed.

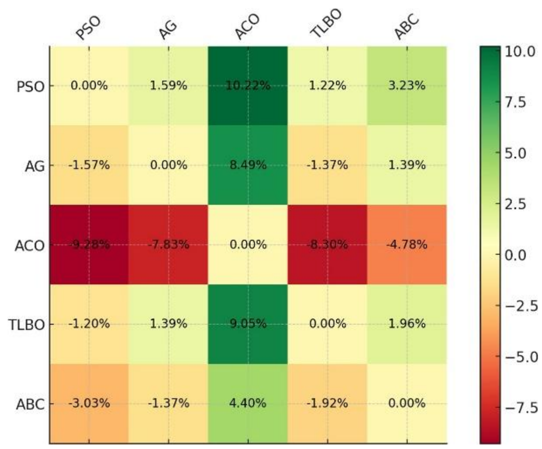
The comparative analysis of the superiority of an algorithm in relation to the other algorithms, considering 4 UAV-BS, is presented in the comparative matrix of Figure 2:

The X and Y axes represent respectively θ and ı in the S(%) calculation, where the PSO has a superiority of 10.22% over the ACO algorithm.

In the graph in Figure 3, the throughput was consistently high for all algorithms, with values around 97 to 100 Mbps. AG and ABC stood out with slightly higher throughputs, especially with 6 UAV-BS. It is clear that the PSO.

Figure 2

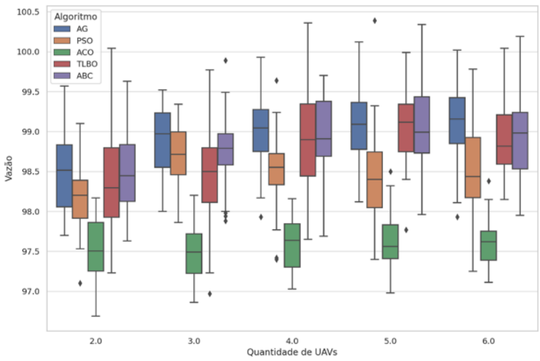
Comparative matrix of algorithm superiority with 4 UAV-BS



At the moment when it has 4 UAV-BS, where it manages to reach the coverage of all users, its results have a smaller variation in relation to the average, that is, the results are almost in the same flow and seeking a less expanded percentile. However, when it is analyzed with 5 UAV-BS, the variance of the PSO leakage results increases, leading to the identification that the increase of UAV-BS in the environment generates a greater signal interference, without generating significant improvement in the analyzed metrics. While the TLBO achieves its best performance in the flow when it manages to cover all its users with 5 UAV-BS, reducing its variation in the flow, assuming the same behavior as the PSO.

Figure 3

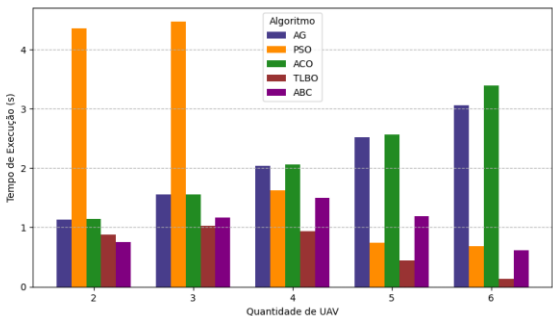
Performance of each algorithm in terms of leakage



The execution time increased as the number of UAV-BS increased, however, from the moment the PSO, TLBO and ABC algorithms began to reach the stopping point in the coverage of all users, as shown in Figure 1, the execution time decreased. The AG and ACO algorithms were not able to have the same convergence and continued to increase the execution time with the increase in the amount of UAV-BS. TLBO and PSO showed relatively low execution times compared to the other algorithms, suggesting superior computational efficiency.

Figure 4

Time-ratio algorithm performance by UAV-BS



The results point to the following characteristics: AG: Solid performance in flow, with loss in performance

I think about the execution time metric.

ABC: Best choice for signal quality (SINR) and leakage, with good user averages connected.

ACO: Balanced performance, but with greater variability and higher run times.

PSO: Good overall performance, but with greater variability and higher execution times.

TLBO: Best choice for consistent overall performance, with excellent average in all metrics and fast run times.

5 CONCLUSIONS

In this article, we compared five metaheurstic algorithms to optimize the positioning of UAV-BS, comparing their performance in the coverage of users distributed in the search space. The experimental results indicated that TLBO and PSO outperformed the other algorithms in the main convergence velocity and user coverage metrics, with TLBO demonstrating a convergence velocity of 0.64s, while PSO has an average velocity of 2.36s. Meanwhile, the PSO achieves complete user coverage with 4 UAV-BS, with a 2% advantage over TLBO and 8% over ACO. The analyses showed that TLBO and PSO compete closely in terms of quality of service and computational cost. These findings contribute to the generalization of UAV-BS positioning approaches, ensuring a diversity of strategies and solution mechanisms, as well as paving the way for future research, including the application of TLBO and PSO in multiobjective optimization problems.

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