Optimization of UAV Positioning: A Comparative Study of PSO, Greedy, and Hybrid Algorithms for Energy Efficiency and Handover Cost

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Abstract

Unmanned Aerial Vehicles (UAVs) are increasingly utilized in swarms, providing effective solutions to a wide range of challenges. This study focused on positioning swarm UAVs as base stations, particularly in disaster scenarios. The positioning process was optimized with respect to energy efficiency and handover cost. Accordingly, an optimization problem was formulated to minimize both the distance to the mission center and the handover cost. To solve this problem, the performance of several algorithms was analyzed, including Particle Swarm Optimization (PSO), Firefly Algorithm (FA), Bat Algorithm (BA), Artificial Bee Colony (ABC) Algorithm, Greedy Algorithm (GA), and a hybrid PSO-Greedy Algorithm approach. The findings revealed that the hybrid algorithm outperformed all other methods. In particular, the hybrid PSO-Greedy Algorithm achieved the best energy performance, with a value of 6.29.

1. Introduction

The utilization of unmanned aerial vehicles (UAVs) has increased substantially in recent years. They have been applied in diverse fields such as agriculture, animal husbandry, military operations, and disaster management, where their use has demonstrated significant benefits. Moreover, when operated in swarms, UAVs are capable of providing more effective solutions to various real-world challenges [1–7]. Multiple UAV systems can be employed as airborne base stations, particularly in scenarios where the demand for base stations increases, such as disaster situations or large-scale public events. Maintaining an optimal position during these operations is of critical importance. In determining such positions, parameters including energy efficiency and handover costs must be carefully considered.

Energy efficiency is a critical consideration for UAVs due to the limited capacity of their batteries. Numerous studies in the literature have addressed the energy efficiency of UAVs, often employing various swarm intelligence algorithms to enhance system performance. However, while energy efficiency has been extensively investigated, research focusing on the joint optimization of handover and energy costs remains limited. This study seeks to address this gap by proposing the use of swarm algorithms and hybrid approaches for optimizing both energy efficiency and handover costs in UAV swarms. UAVs positioned too close to the mission area may lead to increased handover costs and result in signal interruptions.

A considerable number of studies have been published in the literature addressing these topics. According to the 2021 work of Aydin and colleagues, a method was proposed that allows multiple users to rapidly connect to an airborne base station. This approach enhanced security and enabled a greater number of transactions with reduced communication overhead [8]. Du et al. (2025) sought to determine the optimal flight path for a drone to maintain a reliable cellular connection between two locations while minimizing the frequency of base station changes. To achieve this, they developed an algorithm based on graph theory and Lagrangian relaxation for route calculation. The proposed method enabled the drone to operate with fewer base station transitions while preserving connection quality and adhering to time constraints [9].

According to the 2023 review by Jin and colleagues, energy efficiency in UAV communications was examined. The review highlighted the importance of factors such as identifying optimal path routing and stopping points for efficient energy allocation and resource management, developing protocols that minimize energy consumption, and exploring energy harvesting techniques, including solar energy and wireless energy transfer from other devices [10]. Zeng et al. (2017) focused on optimizing flight and communication performance to enhance the energy efficiency of UAVs. They theoretically modeled the energy consumption of a fixed-wing UAV as a function of speed, direction, and acceleration. Based on this model, they defined efficiency in terms of the amount of information transmitted relative to the energy expended during flight. Their analysis suggested that circular flight is more energy-efficient than continuous straight flight. Furthermore, they proposed efficiency improvements through the optimization of flight radius and speed. The study demonstrated that the proposed approach enables longer and more efficient communication performance [11]. In a study conducted in 2019, Cicek and colleagues reviewed the placement of drone base stations. Their review emphasized the importance of developing versatile and fast algorithms to address location-related problems [12].

The structure of our paper is as follows. Section 2 highlights the main contributions of the study. Section 3 introduces the system model, including the experimental setup, the mathematical formulation of the problem, and the optimization algorithms employed in the analysis. Section 4 presents the experimental results and provides a detailed evaluation of the proposed approach in comparison with alternative algorithms. Finally, Section 5 concludes the paper by summarizing the key findings and outlining potential directions for future research.

2. Main Contributions

The main contributions of this study can be summarized as follows:

- The problem of UAV placement is formulated by jointly considering energy efficiency and handover costs.
- The performance of Particle Swarm Optimization (PSO) Algorithm, Artificial Bee Colony (ABC) Algorithm, Firefly Algorithm (FA), Bat Algorithm (BA), and Greedy Algorithm (GA) are compared for solving the optimization problem.
- Among the applied algorithms, the PSO-Greedy hybrid algorithm approach demonstrated successful results and was found to be effective for hybrid use.

With this study, the theoretical aspects of the problem are examined while also providing insights that may be beneficial for practical applications.

3. System Model

The study aims to position UAVs at designated mission centers while simultaneously optimizing both energy efficiency and handover.

3.1. Experimental Setup

The experimental environment consists of UAVs and mission centers deployed within a 100×100 unit area. The mission centers are fixed in the system, and a total of 10 UAVs are assigned to the task. Each UAV has an operational radius of 15 units. Energy consumption depends on the distance between the UAVs and the nearest mission center, and is defined as follows,

$$E_i = \alpha \min_{\mathbf{c}_j \in C} \|\mathbf{p}_i - \mathbf{c}_j\|_2. \tag{1}$$

Here, α is the sampling coefficient and $\min \|.\|$ represents the closest Euclidean distance (with L2 norm) to the mission center. Besides, p_i is the location of the i-th point/vector. c_j represents the j-th center in the cluster. The battery capacity is limited to 200 units, and penalties are applied when this limit is exceeded. The total energy consumption is calculated as,

$$E_{\text{total}} = \sum_{i=1}^{N} E_i. \tag{2}$$

The corresponding battery penalty is expressed as,

$$P_{\text{battery}} = \begin{cases} 0, & E_{\text{total}} \leq E_{\max}, \\ \beta(E_{\text{total}} - E_{\max}), & E_{\text{total}} > E_{\max}. \end{cases} \tag{3}$$

Here $E_{\max}$ is the maximum energy capacity of the UAV base station. In addition, the penalty coefficient is defined by β. It affects how much of a penalty is imposed when the $E_{\max}$ limit is exceeded. Handover cost is introduced when the distance between two UAVs falls below 15 units, which creates a risk of signal collision. It is modelled as,

$$\begin{aligned} d_{ij} &= \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}, \\ H &= \sum_{i=1}^{N} \sum_{j=i+1}^{N} \begin{cases} \dfrac{1}{d_{ij}}, & \text{if } d_{ij} < 15, \\ 0, & \text{otherwise.} \end{cases} \end{aligned} \tag{4}$$

3.2. Problem Formulation

The objective function in this study incorporates energy consumption, handover cost, and battery penalty, and is defined as follows,

$$J(\mathbf{p}_1, \ldots, \mathbf{p}_N) = H + E_{\text{total}} + P_{\text{battery}}. \tag{5}$$

This objective function is minimized using various metaheuristic algorithms, including PSO, FA, BA, ABC, and the Hybrid PSO-GA approach [19, 20].

3.3. Optimization Methods in the Proposed Framework

In this study, PSO, GA, FA, BA, the Hybrid PSO-Greedy Algorithm, and the ABC Algorithm were employed to obtain the optimal solution for the UAV positioning problem.

PSO, originally developed by Kennedy and Eberhart, is a widely used method that seeks the global optimum by exploiting the collective intelligence of particles [13]. The FA, introduced by Yang and inspired by the attraction of fireflies to light, is capable of performing effective exploration in the solution space [14]. Although the GA provides rapid solutions by making locally optimal decisions at each step, it often deviates significantly from the global optimum. The BA, also proposed by Yang, is an optimization technique that models the orientation behavior of bats using their biological sonar systems [15].

The Hybrid PSO-GA combines the global search ability of PSO with the fast convergence property of the Greedy Algorithm approach, aiming to produce more balanced results [16, 17]. Finally, the ABC Algorithm, developed by Karaboga, mimics the foraging behavior of honey bee colonies and is particularly effective in continuous optimization problems [18].

The comparative evaluation of these algorithms provided insights into which approaches yield more optimal solutions in the context of UAV positioning.

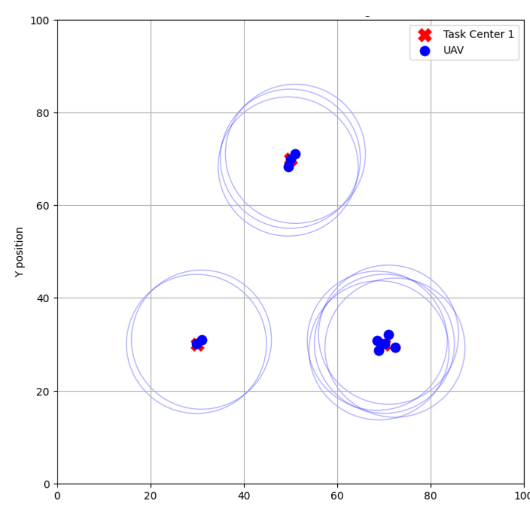

Figure 1. Illustration of UAV placement and corresponding coverage regions optimized using PSO Algorithm.

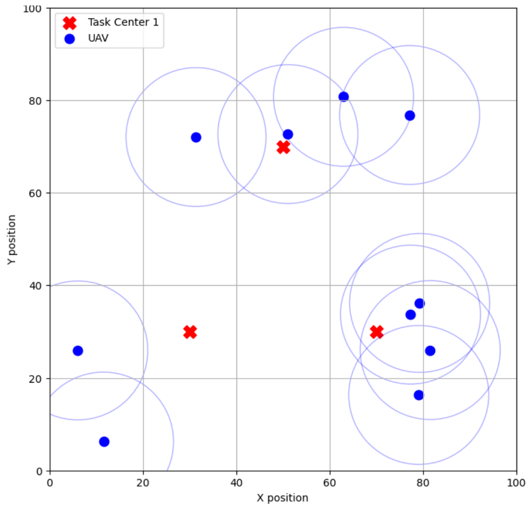

Figure 2. UAV locations and coverage areas obtained through the Firefly Algorithm.

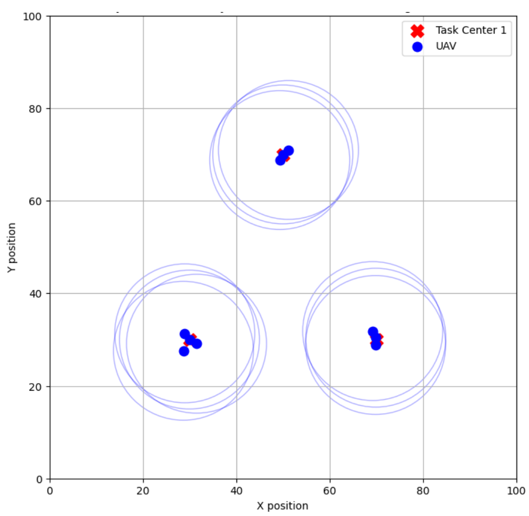

Figure 3. UAV locations and coverage areas obtained using the Hybrid PSO-Greedy Algorithm.

4. Experimental Results

In this section, the results obtained from the algorithms used for UAV positioning and airborne base stations are presented. The experimental result obtained with the PSO algorithm is illustrated below, in Figure 1. This figure shows the UAV positioning and corresponding coverage areas achieved with the PSO algorithm [19, 20]. A uniform coverage distribution was obtained in this case.

The result obtained with the FA is illustrated in Figure 2. As shown in Figure 2, the FA provided coverage for two out of three tasks, while one task remained uncovered. The result obtained with the Hybrid PSO-GA is presented in Figure 3. As shown in Figure 3, the hybrid approach successfully combined the strengths of PSO and the GA, achieving a more balanced and effective distribution of UAVs while providing improved coverage and handover performance. The output of the GA is presented in Figure 4. According to Figure 4, the GA achieved coverage areas in a more structured and effective manner compared to the other algorithms.

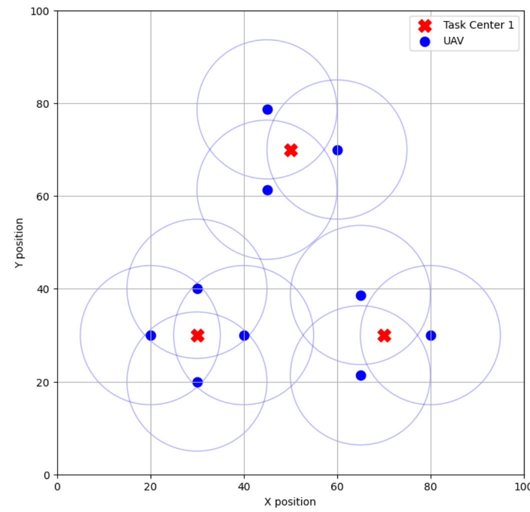

Figure 4. UAV positioning and corresponding coverage areas determined using the Greedy Algorithm.

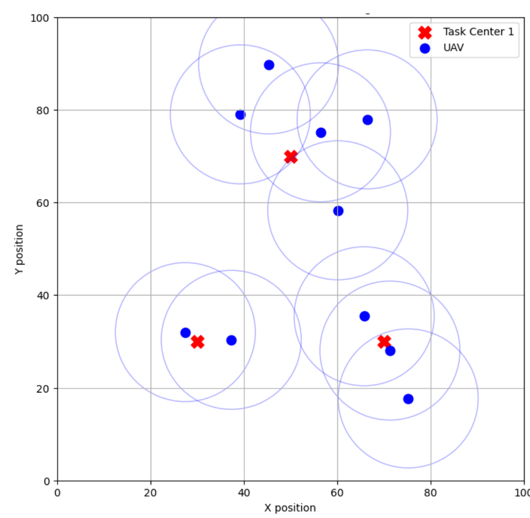

Figure 5. UAV positioning and corresponding coverage areas obtained through the Artificial Bee Colony Algorithm.

The output of the ABC Algorithm is shown in Figure 5. Figure 5 demonstrates that the ABC algorithm successfully obtained coverage for the assigned tasks. The result obtained with the BA is depicted in Figure 6. As illustrated in Figure 6, the BA achieved coverage in two of the three tasks, while one task was not included in the coverage area.

To enhance the clarity of the simulation outcomes and provide a more comprehensive demonstration of the swarm intelligence algorithms' behavior, the corresponding code was executed three independent times. The results obtained from the first, second, and third executions are respectively presented in Tables 1, 2, and 3.

Table 1 presents the total cost results obtained from the first, second, and third executions of the algorithms, along with their corresponding averages. As indicated in the table, the hybrid algorithm yielded the lowest average cost among all methods evaluated.

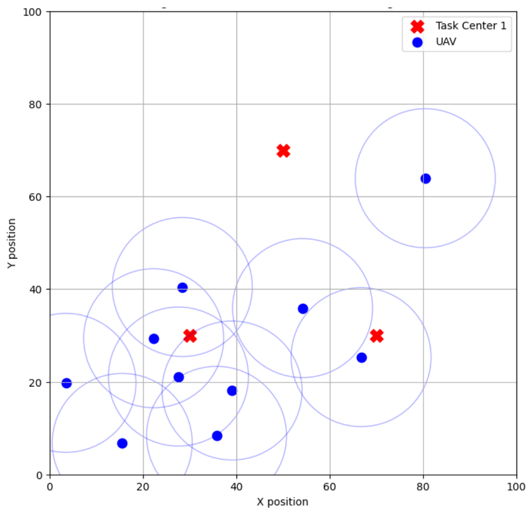

Figure 6. UAV positioning and coverage regions determined via the Bat Algorithm.

Table 1. Comparative analysis of algorithmic performance based on average total cost across three simulation runs.

Algorithm	1st Run	2nd Run	3rd Run	Average
PSO	12.80	15.73	13.63	14.05
FA	98.18	84.31	80.48	87.66
GA	50.28	50.28	50.28	50.28
BA	87.54	82.47	84.03	84.68
ABC	52.97	53.00	55.98	53.98
Hybrid	12.33	11.76	11.72	11.94

Table 2 presents the handover cost results obtained from three independent runs of the algorithms, along with their average values. Among the evaluated methods, the GA algorithm achieved the lowest average handover cost.

Table 3 presents the energy consumption results obtained from three independent runs of the algorithms, along with their average values. The hybrid algorithm demonstrated the lowest average energy consumption among the methods evaluated.

The quantitative outputs of the algorithms are summarised in Table 4. As observed in Table 4, the Hybrid PSO-GA operates with the lowest total cost. Although its handover cost is slightly higher compared to some alternatives, it remains lower than that of PSO. In terms of energy consumption, the hybrid model also demonstrates the most favorable performance.

5. Conclusion

In this study, the positioning of UAVs with respect to mission centers was investigated. An optimization framework was developed that jointly considers energy efficiency and handover costs. Within this framework, experiments were conducted using several swarm intelligence algorithms inspired by nature. The results showed that PSO performed effectively in terms of energy efficiency and positioning. Furthermore, the GA produced a regular distribution around the target, and when combined in a hybrid form with PSO, improvements were observed in the overall performance. This study aims to contribute to the literature by presenting experimental results on energy efficiency and handover costs using metaheuristic algorithms.

Table 2. Comparative evaluation of algorithmic performance based on average handover cost over three simulation trials.

Algorithm	1st Run	2nd Run	3rd Run	Average
PSO	6.38	8.04	6.74	7.05
FA	0.40	0.33	0.68	0.47
GA	0.28	0.28	0.28	0.28
BA	0.58	0.82	0.40	0.60
ABC	1.62	2.33	0.65	1.53
Hybrid	5.23	5.86	5.85	5.65

Table 3. Average performance of the algorithms across three independent runs in terms of energy consumption.

Algorithm	1st Run	2nd Run	3rd Run	Average
PSO	6.42	7.69	6.89	7.00
FA	97.79	83.98	79.81	87.19
GA	50.00	50.00	50.00	50.00
BA	86.96	81.65	83.63	84.08
ABC	51.35	50.67	55.33	52.45
Hybrid	7.10	5.89	5.87	6.29

Table 4. Comparison of algorithms in terms of average total cost, handover cost, and energy consumption.

Algorithm	Average Total Cost	Average Handover Cost	Avarege Energy Consumption
PSO	14.05	7.05	7.0
FA	87.66	0.47	87.19
GA	50.28	0.28	50.00
BA	84.68	0.60	84.08
ABC	53.98	1.53	52.45
Hybrid	11.94	5.65	6.29

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