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Placement optimization of multiple UAVs for energy-efficient maximal user coverage

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ABSTRACT

This paper proposes a deterministic Global Optimization Algorithm (GOA) for UAV-assisted communications, developed as an enhancement to the benchmark Two-Stage Optimization Algorithm (TSOA). The algorithm simultaneously addresses the dual objectives of maximizing ground user (GU) coverage and minimizing total power consumption in multiple UAV systems. Unlike existing literature, which predominantly relies on heuristic approaches, GOA provides a more precise and systematic solution to achieve optimal performance. Comprehensive simulations demonstrate that GOA achieves a 3.68 % increase in coverage count versus SOA under clustered GU distributions while delivering energy savings approximately 2.47 % (uniform) and 2.6 % (clustered) relative to the TSOA benchmark. Crucially, these efficiency gains are realized while maintaining superior GU coverage maximization versus all benchmarked methods. Both numerical results and visual analyses conclusively validate the proposed algorithm's outperformance of existing benchmarks.

1. Introduction

The rapid advancement of urbanization and the exponential increment of Internet of Things (IoT) devices have strained terrestrial networks, challenging their ability to satisfy the increasing demand for diverse connectivity [1]. The situation deteriorates rapidly during emergencies, when vulnerable ground base-stations (GBs) that normally sustain connectivity can fail catastrophically, leaving entire regions without communication. The advent of Unmanned Aerial Vehicles (UAVs) has revolutionized telecommunications, offering rapid deployment in scenarios where traditional infrastructure as failed.

UAV-assisted telecommunication plays a crucial role in disaster response, rural connectivity, and large-scale events by providing temporary yet reliable coverage. Their agility, mobility, and cost-effectiveness, make them a promising alternative for applications such as IoT sensor networks and emergency response [1,2]. This versatility has driven demand for UAV-based solutions that circumvent the physical and logistical constraints of ground infrastructure. Despite these advantages, UAVs in wireless telecommunications face significant challenges. Consequently, the studies of [1,4–6] stress the importance of customizing UAV placement strategies to meet immediate wireless communication needs in the given region.

According to [2,3,6–9], there are two main modes of UAV assisted communication: flying and hovering. The flying communication focuses on optimizing the trajectory of UAVs to enable instantaneous data collection and communication while maintaining connectivity with ground users (GUs) during motion. Conversely, the hovering communication mode concentrates on determining the optimal stationary positions for UAVs to facilitate continuous monitoring or data relaying from a fixed location. The strategic positioning of UAVs is crucial for enhancing system performance and network revenue, as it influences key communication attributes such as coverage, capacity, connectivity, and efficiency, as noted by researchers in [6].

To the best of our knowledge [6], presents the most recent comprehensive survey on 3D placement optimization in UAV-assisted communication. A key contribution of this study is the use of taxonomy to classify the literature based on diverse optimization objectives, problem formulations, and required solution strategies. Conventionally,

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the approaches to optimizing objective functions can be categorized into heuristic algorithms and exact (deterministic) algorithms, as shown in Tables 12 and 13 of [6]. The authors enumerate several common optimization objectives, including ground coverage, number of covered users, data rate/throughput, power transmission, and energy consumption. These optimization objectives typically derive from performance metrics measured before and after UAV deployment.

Early research efforts [4,5,13] concentrated on hovering placement of a single-UAV with the objective of ground users (GUs) coverage and power consumption of UAVs' endurance. Consequently, numerous recent survey articles have emerged based on the formulations presented within the former studies. These works have synthesized and summarized air-to-ground (AtG) signal propagation models for both line-of-sight (LoS) and non-line-of-sight (NLoS) in wireless communication. Among these, the most fundamental and seminal contributions are the Probabilistic LoS propagation modes categorized and summarized in studies [2,3,6].

Building on these foundations, many researchers are expanding their investigations into multiple UAVs by either altering environmental conditions or incorporating constraints to enhance innovation. However, the complexity of many derivative algorithms increases with these added constraints and conditions, often leading to the adoption of heuristic algorithms that yield suboptimal results.

For instance, study [1] developed an obstacle-aware extension of the LoS and NLoS propagation models, employing beamforming techniques to mitigate signal obstruction. Consistent with this trend, studies [10,11] have incorporated advanced radio wave techniques to enhance ground user coverage performance. While [10] focuses on special antenna configurations, [11] adopts a multiple beam association approach. Similarly, Sabzehali et al [12] address deployment of multiple UAVs to optimize coverage and power consumption. However, the formulated problem exhibits NP-Hard computational complexity, necessitating the adoption of heuristic algorithms. Nevertheless, the primary objective of these researchers was to minimize the required number of UAVs to subsequently enhance coverage effectiveness. A recurring limitation across these studies is their cardinal objective of minimizing UAV deployment numbers for coverage efficiency. This emphasis neglects the possibility that prioritizing power consumption optimization could generate more significant coverage improvements than those attainable through mere reductions in UAV quantity.

Researchers in [14] develop a sequential UAV deployment strategy wherein each drone is placed iteratively, with the coverage influence on ground users being eliminated after each placement before deploying the next UAV. This approach aligns conceptually with our subsequently discussed Sequential Optimization Algorithm (SOA) framework.

Consequently, we propose two novel algorithms for the joint optimization of multiple UAV systems, addressing both optimal deployment and energy efficiency objectives in [3,4]. The first algorithm, termed the Two-Stage Optimization Algorithm (TSOA), follows a sequential optimization paradigm that first maximizes user coverage before minimizing UAV energy consumption. In contrast, the second algorithm is designated as the Global Optimization Algorithm (GOA) that introduces a unified optimization framework that simultaneously addresses both coverage maximization and energy minimization through an integrated formulation, thereby achieving globally optimal solutions. In essence, the key contributions of this work are twofold:

1) We adopted a global observation approach to consider and solve the dual optimization problem;
2) We devised a novel optimization formula that synchronously addresses the covered user count and the energy efficiency of UAVs.

2. System model

To ensure comparative consistency with established research, we adopt the identical modeling methodology as [4,5,14], employing the same LoS and NLoS propagation models. As depicted in Fig. 1, both UAVs and the GUs are comprising multiple entities. We use N for the number of UAVs and K for the number of GUs, and they both are positive integers. The horizontal coordinates of the n-th UAV are denoted as (x_{D_n}, y_{D_n}), while those of the k-th GU are (x_k, y_k). The complete set of UAV horizontal coordinates is represented by $\mathscr{U}$, and the set of GU coordinates by $\mathscr{G}$.

Formal studies in [4,5] have introduced a methodology for placing a single-UAV in 3D space, decoupling horizontal and vertical coordinates by using optimal elevation angles. In this study, we expand upon this method to accommodate a scenario involving multiple drones, as illustrated Fig. 1. Alzenad et al [4] have developed and validated this framework through experiments in four geographical environments: suburban, urban, dense-urban, and high-rise urban. These classifications are based on the statistical parameters of urban environments documented by the International Telecommunication Union (ITU) [5]. According to the theoretical framework proposed by the author of [4], each type of environment corresponds to an optimal UAV altitude associated with a specific optimal elevation angle. The authors of [5] have derived precise optimal elevation angle values for these four environmental conditions, as documented in their studies, Suburban ($\theta_S = 20.34^\circ$), Urban ($\theta_U = 42.44^\circ$), Dense Urban ($\theta_D = 54.62^\circ$), and High-rise Urban ($\theta_H = 75.52^\circ$).

The optimal elevation angles for these environments are denoted as $\theta \in \{\theta_S, \theta_U, \theta_D, \theta_H\}$. Similarly, the corresponding optimal altitudes for multiple UAVs are defined as $H \in \{H_S, H_U, H_D, H_H\}$. According to equation of $R = \frac{H}{\tan\theta}$, the maximum coverage radius set is $R \in \{R_S, R_U, R_D, R_H\}$.

2.1. Maximum coverage problem formulation

In the first stage of TSOA, the objective is to horizontally place multiple UAVs simultaneously in a designated geographic area and to maximize the coverage of GUs. Nevertheless, when a GU is in the overlapping coverage region (CR) of two or more UAVs, it may result in duplicated counting of this GU due to the objective of the maximum coverage problem. In the first stage of TSOA, the objective is to horizontally place multiple UAVs simultaneously in a designated geographic area and to maximize the coverage of GUs. Nevertheless, when a GU is in the overlapping CR of two or more UAVs, it may result in duplicated counting of this GU due to the objective of the maximum coverage problem

To address this problem, we introduce the decision variable $t_{k_n} \in \{0, 1\}$ along with two constraints as described below to serve a dual purpose: first, to delineate the coverage status of the k-th GU by the n-th

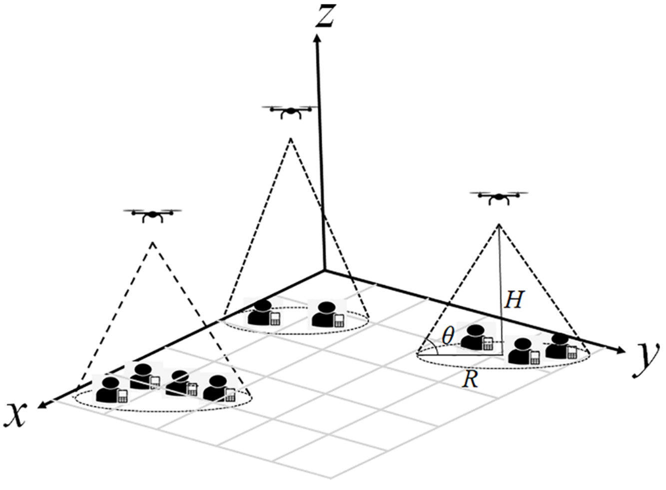


Fig. 1. 3D coverage geometry of multiple UAVs deployment.

UAV; and second, to regulate the counting assessment of the k-th GU, ensuring non-duplication of counts. This approach presents significant advancement over the binary variable as described in [4]. Firstly, we extend the constraint condition for multiple UAVs based on the optimal 2D placement inequality for a single-UAV as presented in [4], as:

$$(x_k - x_{D_n})^2 + (y_k - y_{D_n})^2 \le \mathrm{R}^2 + M(1 - t_{k_n}). \tag{1}$$

where M is a large constant, ensuring that when $t_{k_n} = 0$, the inequality holds true for the k-th GU regardless where the n-th UAV is placed, and the k-th GU is not counted under the coverage of the n-th UAV. It is noted that $t_{k_n} = 1$ indicates that the k-th GU is counted under the coverage of the n-th UAV, and the inequality (1) reduces to:

$$(x_k - x_{D_n})^2 + (y_k - y_{D_n})^2 \le R^2. \tag{2}$$

which is only satisfied when the k-th GU is within the CR of the n-th UAV. Regardless of the quantity of UAVs in set $\mathscr{U}$, the k-th GU should be included at most once in the coverage count. Consequently, we articulate a constraint as:

$$0 \le \sum_{n\in\mathscr{U}} t_{k_n} \le 1, \forall_k \in \mathscr{G}. \tag{3}$$

Based on (1), (2) and (3), the Maximum Coverage Problem can be formulated as:

$$\underset{x_{D_n}, y_{D_n}, \mathrm{R}_n, t_{k_n}}{\text{Maximize}} \sum_{\substack{k\in G \\ n\in U}} t_{k_n}$$

Subject to

$$(x_k - x_{D_n})^2 + (y_k - y_{D_n})^2 \le R^2 + M(1 - t_{k_n}), \forall_k \in \mathscr{G}, \forall_n \in \mathscr{U},$$

$$0 \le \sum_{n\in\mathscr{U}} t_{k_n} \le 1, \forall_k \in \mathscr{G},$$

$$t_{k_n} \in \{0, 1\}, \forall_k \in \mathscr{G}, \forall_n \in \mathscr{U}. \tag{4}$$

The problem defined by (4) is a Mixed Integer Non-linear Programming (MINLP). Notably, the MOSEK optimization solver [15] is effective to tackle this problem. After solving the initial optimization problem, the horizontal coordinates of UAVs are cataloged in the solution set denoted as U^{max}, and the 3D coordinates of the n-th UAV are denoted as $(H, x_{D_n}^{max}, y_{D_n}^{max})$. The most significant outputs are quantities and coordinates of those covered GUs saved into collection, which is inherently a subset of $\mathscr{G}$, formally represented as $\mathscr{G}^{cover} \subseteq \mathscr{G}$.

2.2. Minimum energy problem formulation

The second stage of the TSOA intends to minimize the effective coverage range by reducing the transmit power of multiple UAVs, while ensuring all GUs in $\mathscr{G}^{cover}$ are covered. Therefore, the second stage problem is a minimum covering circle problem in general mathematics. To address the challenge of re-adjusting the horizontal coordinates and radii of multiple UAVs simultaneously while ensuring the covered GUs in $\mathscr{G}^{cover}$ are retained, we extend the approach described in [4] from a single-UAV to multiple UAVs, and formulate the Minimum Energy Problem as:

$$\underset{x_{D_n}, y_{D_n}, \mathrm{R}_n}{\text{Minimize}} \sum_{n\in\mathscr{U}} \mathrm{R}_n$$

Subject to

$$(x_k - x_{D_n})^2 + (y_k - y_{D_n})^2 \le R_n^2 + M(1 - t_{k_n}),$$

$$\forall_k \in \mathscr{G}^{cover}, \forall_n \in \mathscr{U},$$

$$1 \le \sum_{n\in\mathscr{U}} t_{k_n}, \forall_k \in \mathscr{G}^{cover},$$

$$t_{k_n} \in \{0, 1\}, \forall_k \in \mathscr{G}^{cover}, \forall_n \in \mathscr{U}. \tag{5}$$

where the constraints in (5) ensure the coverage of each GU in $\mathscr{G}^{cover}$. Similarly, problem (5) represents another MINLP challenge and serves as a further refinement following problem (4). Here, the selection value for any k is constrained within the newly defined set $\mathscr{G}^{cover}$. In response to this, the MOSEK optimization solver can still be applied to find a solution. Upon the completion of the optimization process, the collection of horizontal coordinates for the UAVs is denoted by U^{min}, and the 3D coordinates of the n-th UAV are specified as $(H, x_{D_n}^{min}, y_{D_n}^{min})$. Additionally, the transmit radii of the UAVs are recalculated, with the optimized transmit radius of the n-th UAV represented by R_n^{opt}. Moreover, the set aggregates the overall quantity of GUs encompassed within the CR of the multiple UAVs.

2.3. Unified optimization formulation

In this subsection, the GOA problem formulation serves as a unified integration of two distinct problems of the TSOA algorithm. According to the duality principle in optimization problems, different optimization directions can be unified through the application of inverse operation formulas. For instance, ''Minimization'' and ''Maximization'' are inverse operations of each other. Within this framework, we employ the ''Maximize'' optimization method to concurrently optimize the function variables t_{k_n} and R_n in problems formulated in subsections max and min, respectively. This approach adopts a global consideration of problem-solving, by addressing the causal relationship between two variables and the impact of variations in R_n on the coverage quantity of t_{k_n} variable. As a result, this unified formulation not only facilitates the simultaneous optimization of both function variables but also improves the overall efficiency of the algorithm and simplifies the involved processes. Consequently, expression (6) is derived from (4) and (5), as:

$$\underset{x_{D_n}, y_{D_n}, \mathrm{R}_n, t_{k_n}}{\text{Maximize}} \left(\sum_{\substack{k\in G \\ n\in U}} t_{k_n} - \sum_{n\in\mathscr{U}} \mathrm{R}_n \,/\, \mathrm{R} \right)$$

Subject to

$$(x_k - x_{D_n})^2 + (y_k - y_{D_n})^2 \le R_n^2 + M(1 - t_{k_n}), \forall_k \in \mathscr{G}, \forall_n \in \mathscr{U},$$

$$0 \le \sum_{n\in\mathscr{U}} t_{k_n} \le 1, \forall_k \in \mathscr{G},$$

$$t_{k_n} \in \{0, 1\}, \forall_k \in \mathscr{G}, \forall_n \in \mathscr{U}. \tag{6}$$

The core parametric innovation lies in the unified objective function for problem (6), $\sum_{\substack{k\in G \\ n\in U}} t_{k_n} - \sum_{n\in\mathscr{U}} R_n/R$. This composite function integrates two distinct optimization objectives. The first term, $\sum_{\substack{k\in G \\ n\in U}} t_{k_n}$ maximizes the coverage metric, directly aligning with the objective of problem (4), where the binary variable t_{k_n} indicates GUs' coverage. The second term, $-\sum_{n\in\mathscr{U}} R_n/R$, performs as a normalized energy proxy metric, which effectively reformulates the energy minimization objective Minimum($\sum_{n\in\mathscr{U}} R_n$) from problem (5) into a maximization framework within the unified expression. Practically, the actual coverage radius R_n deployed by each UAV inherently deviates from its maximum achievable radius R due to heterogeneous GUs distribution patterns. Consequently, normalization by R ensures both terms are dimensionless and numerically comparable, eliminating dominance of one objective over the other. Like the other two formulations above, the formulation (6) also falls under the category of MINLP and can be effectively solved using the MOSEK solver. As a result of the optimization, we can obtain both the optimal radius and 3D coordinates of the n-th UAV represented as R_n^{opt} and $(H,\ x_{D_n}^{unified},\ y_{D_n}^{unified})$ respectively. Meanwhile, the covered GUs are stored into the $\mathscr{G}^{cover}$.

3. Simulation results

To evaluate the performance of the proposed TSOA and GOA algorithms against the existing SOA algorithm in simulations, we utilize Poisson Point Process and Thomas Point Process for GU distribution, with the total number of GUs following a Poisson distribution as detailed in [4,5]. This allows us to establish both uniform and clustered GU distribution patterns. Adhering to the GU density parameter (denoted as λ) specified in the Simulation Sections of prior studies [4,5], we employ a random generation method for the number and distribution of GUs. This method ensures that the average number of GUs aligns with the configurations in Table 1. Consequently, these parameter settings are adopted from the Urban scenario.

We define the path loss threshold PL as the difference between maximum and minimum transmit. As shown in Table 1, $PL = P^{max}$ - P^{min} = 100 dBm. Following the formulars of the optimal elevation angle, path loss threshold, and maximum radius found in [4,5], we derive the UAV's maximum coverage radius in Urban environment as $R_U = 0.702$ km. By using geometric equation $R = \frac{H}{\tan\theta}$, the corresponding optimal UAV's altitude is $H_U = 0.642$ km. Thus, these three parameters are now fully specified the inputs required for TSOA and GOA as shown in Fig. 2.

The simulation results for single-UAV and dual-UAV placements scenarios are depicted in Fig. 3 and Fig. 4, respectively. The dual-UAVs configuration is representative of scenarios involving multiple UAVs. To ensure the reliability and statistical robustness of the results, each algorithm is simulated 100 times, with average performance metrics presented.

In the single-UAV scenarios, the TSOA algorithm involves a one-time horizontal placement followed by a single reduction of the CR, following the SOA approach. In contrast, TSOA simultaneously places both UAVs and subsequently contracts the CR collectively, differing from the sequential placement and sequential reductions process executed by SOA. Besides, the GOA algorithm combines both UAV placement and CR reductions into an unified optimizing process.

Fig. 3(a) demonstrates the percentage of covered GUs by the existing SOA and GOA algorithms, compared to the total number of initially generated GUs. Both SOA and GOA have almost the same performance for uniform or clustered distributions, respectively. Because these algorithms are targeted to maximize the number of GUs covered, resulting in marginal differences in coverage outcomes.

Fig. 3(b) presents the percentage reduction of CR for a single-UAV placement, comparing the performance of the SOA and the GOA under both uniform and clustered GU distributions. The results demonstrate that the GOA outperforms the SOA, reducing the CR by 2.35 % and 2.01 %. This advantage is attributed to GOA's integrated optimization framework, which simultaneously maximizes GU coverage and minimizes CR scale, enabling a globally optimized solution. In contrast, SOA employs a sequential optimization procedure, prioritizing coverage maximization followed by CR minimization, leading to marginally suboptimal overall outcomes. Consequently, the comparative results presented in Fig. 3 indicate GOA's general outperformance of SOA for this specific case.

Table 1
Urban environment simulation parameters.

Parameters	Values
Region Size	4 km × 4 km
Ground User Density (λ)	6 users/km2
S-curve Parameter a [4]	9.6117e+00
S-curve Parameter b [4]	1.5806e-01
Mean Additional Losses for Line-of-Sight (η_{LoS})	1 dB
Mean Additional Losses for Non-Line-of-sight (η_{NLoS})	20 dB
UAV Maximum Transmission Power (P^{max})	30 dBm
Ground User Minimum Receiving Strength (P^{min})	−70 dBm
UAV Optimal Elevation Angle (θ_U)	42.44°
UAV Maximum Coverage Radius (R_U)	0.702 km
UAV Optimal Height (H_U)	0.642 km
Electromagnetic Wave Frequency (f_c)	2 GHz

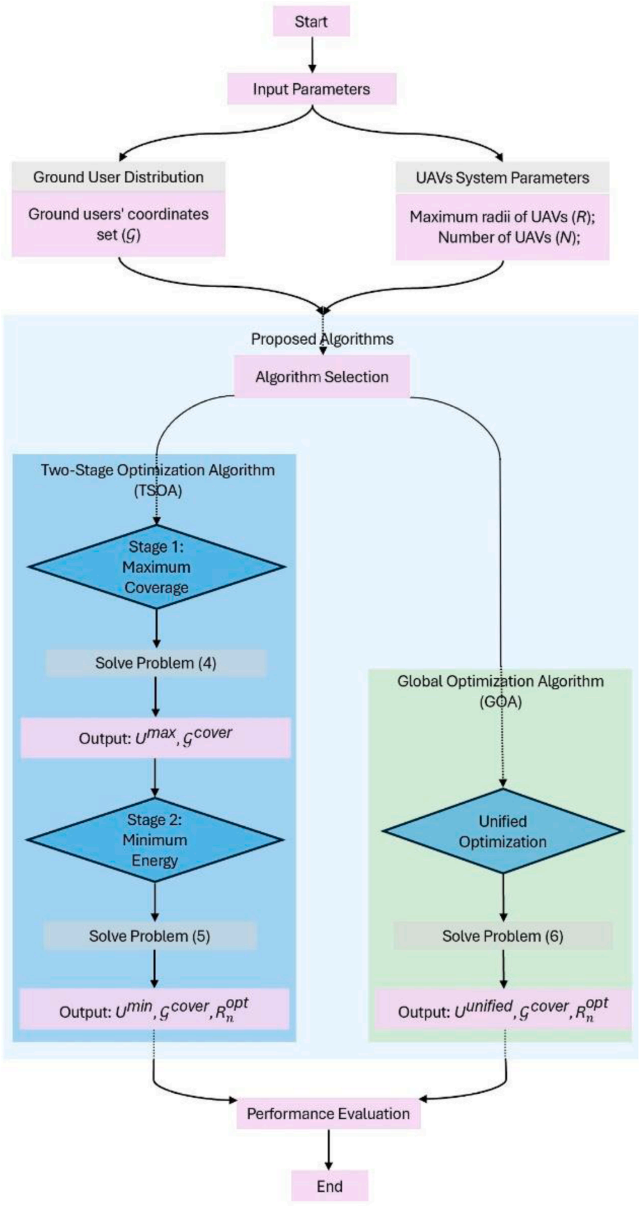


Fig. 2. The flowchart of proposed TSOA and GOA.

Fig. 4(a) presents the GU coverage performance in the dual-UAV scenarios, comparing all three algorithms: SOA, TSOA, and GOA. The primary distinction in this setting stems from the operational strategies of SOA and TSOA. Specifically, SOA executes UAV placement and CR reduction sequentially for each UAV, while TSOA employs a simultaneous strategy, performing the placement for both UAVs collectively and then concurrently reducing the radii CR.

Under a uniform GU distribution, the coverage performance of the three algorithms is nearly indistinguishable, as shown in Fig. 3(a) for the single-UAV case. This similarity arises because optimal UAV placement leads to non-overlapping CRs, making the placements effectively independent. As a result, sequential optimization and simultaneous optimization approaches are functionally equivalent in maximizing coverage

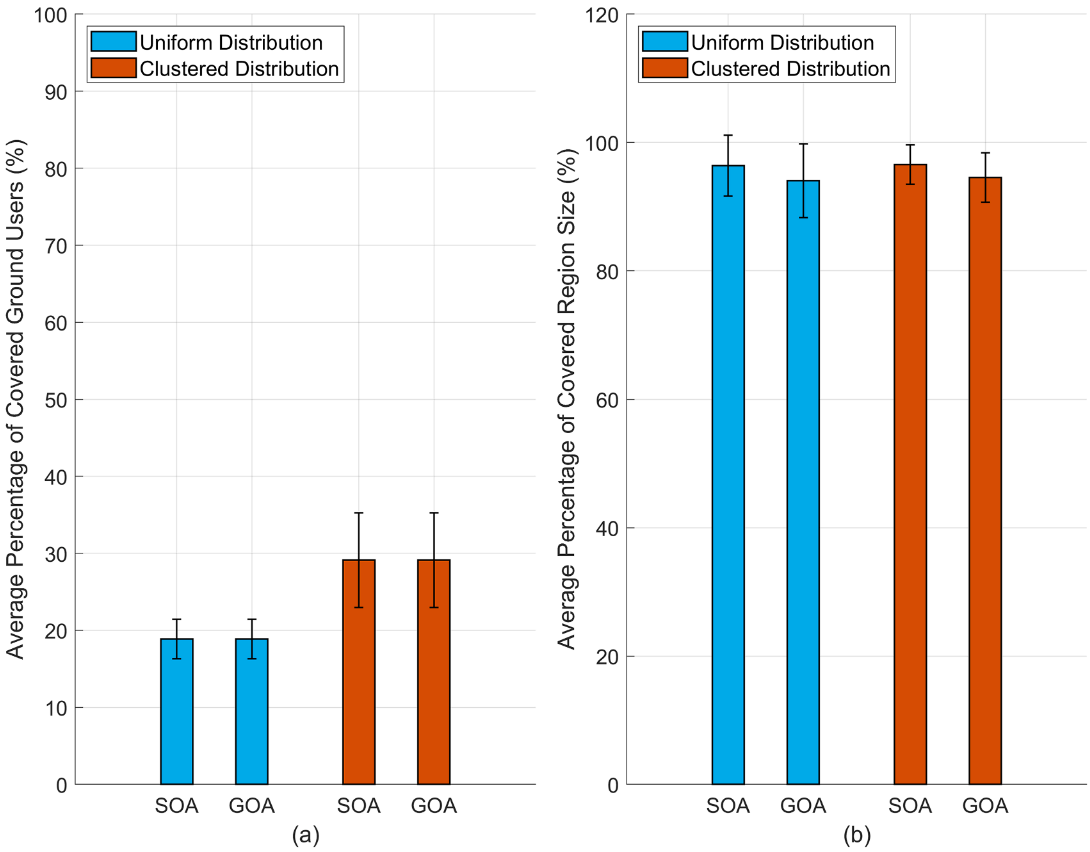


Fig. 3. Performance of SOA, GOA algorithms in the single-UAV scenarios. (a) Average percentage of covered ground users. (b) Average percentage of covered region size.

performance in this scenario.

Conversely, in clustered GU distributions, the TSOA and GOA algorithms exhibit slightly outperformance compared to the SOA algorithm, attributed to user distribution heterogeneity, a concept discussed in [4]. This performance difference arises because, in clustered scenarios, the CR of the two UAVs tend to overlap, introducing a correlation between their placements. In the SOA algorithm, GUs covered by the first UAV are removed from consideration before placing the second UAV, thereby modifying the spatial heterogeneity of the remaining GUs. In contrast, both TSOA and GOA determine UAV placements simultaneously based on the original, unaltered GU distribution, enabling a more holistic and coordinated optimization strategy. Notably, TSOA and GOA achieve comparable average GU coverage, as both are designed to maximize the number of covered GUs. Therefore, the covered GU's quantity of TSOA and GOA algorithms are 3.68 % higher than that of the SOA algorithm in Fig. 4(a).

As shown in Fig. 4(b), under uniform GU distributions, both SOA and TSOA demonstrate comparable performance in radii reduction optimization, while GOA achieves a substantially more obvious CR decrease. This corresponds to energy savings improvements of 2.67 % and 2.47 % over SOA and TSOA, respectively. However, under clustered GU distributions, GOA presents only a marginal 0.57 % CR reduction relative to SOA. This attenuated improvement stems from GOA's inherent computational advantage, because GOA initially deploying UAVs to encompass a larger quantity of GUs, which constrains the percentage reduction achievable during simultaneous radius optimization. Crucially, despite this limited CR reduction, GOA maintains coverage parity with TSOA while simultaneously achieving a notable 2.6 % enhancement in energy efficiency than TSOA.

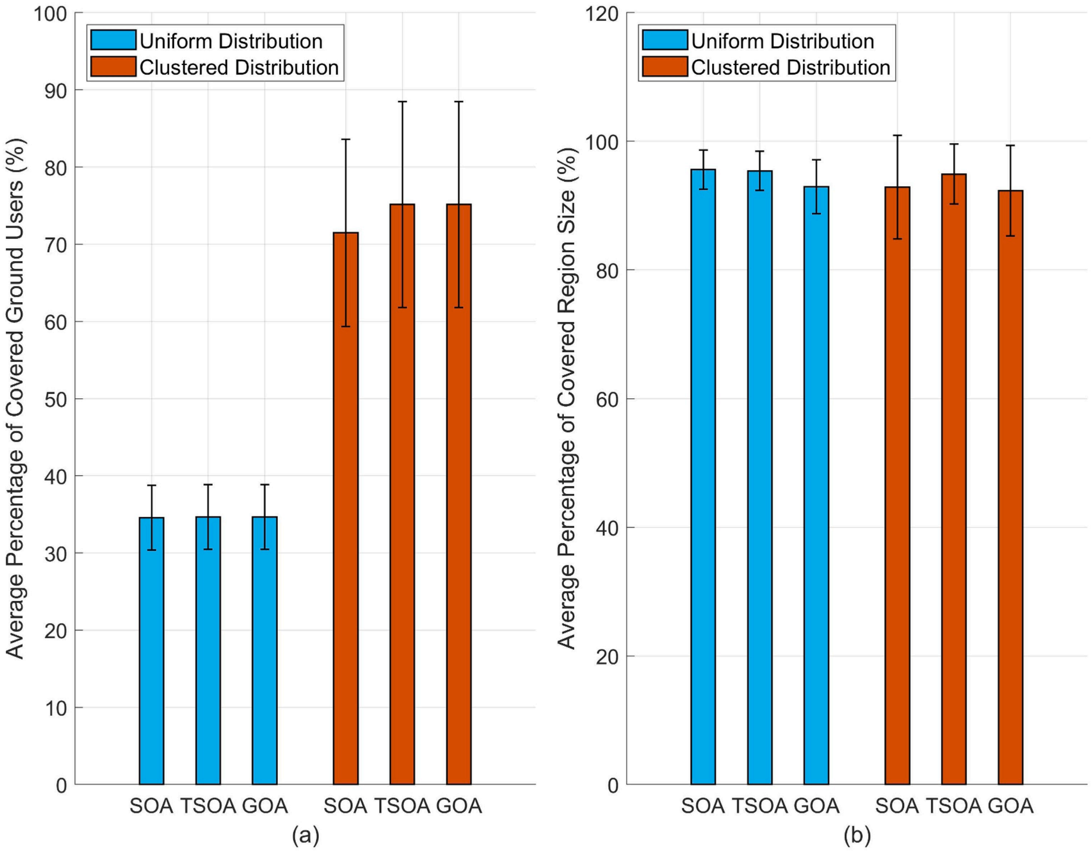
Returning to the analysis of the bar charts in Fig. 4, the GOA algorithm demonstrates the most favorable performance among the assessed algorithms. Accordingly, the comparative effectiveness of the algorithms can be ranked as SOA < TSOA < GOA. It is equally important to note that, in our simulations, the number of GUs follows a Poisson distribution. This stochastic variability leads to larger fluctuations in the standard deviations, as reflected by the error bars in Fig. 4(a) and Fig. 4 (b).

4. Conclusion

This paper presents an integrated optimization framework for decoupled multiple UAVs placement, building upon and unifying a global optimization perspective. Our holistic approach simultaneously coordinates distinct optimization stages, achieving measurable performance gains. The simulation results indicated that the GOA algorithm achieves advance performance than both SOA and TSOA benchmarks. Significantly, GOA was derived through an evolutionary refinement of the TSOA framework. Each optimization algorithm was evaluated through 100 times independent simulation, yielding the statistically significant comparative results.

5. Future work

While our study introduces a deterministic approach for optimizing static UAV placement, future research will address aerial-to-ground factors on GUs' mobility and sudden increment of traffic demand. To enhance practicality, it is essential to incorporate terrain heterogeneity, physical obstructions, and meteorological factors like signal attenuation due to precipitation and the impact of humidity on signal propagation. To navigate these complexities, the reinforcement learning for real-time deployment adjustments and graph neural networks for obstacle-aware path planning, possibly can address computational challenges and in



(a) (b)

Fig. 4. Performance of SOA, TSOA and GOA algorithms in the dual-UAV scenarios. (a) Average percentage of covered ground users. (b) Average percentage of covered region size.

large-scale dynamic scenarios. These extensions would strengthen operational resilience meanwhile bridging the gap between theoretical optimization and real-world deployment feasibility.

CRediT authorship contribution statement

Chen Zhang: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Conceptualization. **Xiang Gui:** Writing – review & editing, Supervision, Project administration, Formal analysis, Data curation, Conceptualization. **Gourab Sen Gupta:** Writing – review & editing, Supervision, Project administration. **Syed Faraz Hasan:** Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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