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UAV Swarm Mission Planning and Load Sensitivity Analysis Based on Clustering and Optimization Algorithms

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Abstract: Unmanned aerial vehicle (UAV) swarms offer unique advantages for area search and environmental monitoring applications. For practical deployments, determining the optimal number of UAVs required for a given task and defining key performance metrics for the platforms and payloads are crucial challenges. This study aims to address mission planning and performance optimization for cooperative UAV swarm search scenarios. A new clustering algorithm is proposed, integrating enhanced clustering techniques with ant colony optimization, particle swarm optimization, and crow search optimization. This jointly optimizes and validates the UAV numbers and coordinated trajectories. Sensitivity analysis and indicator optimization further examine specific scenarios to quantify platform and sensor factors influencing search efficiency. Lastly, sensitivity analysis and performance indicator optimization are conducted in specific scenarios. The modular algorithmic components and modeling techniques established in this work lay a foundation for continued research into real−world mission−based swarm optimization.

Keywords: UAV cluster; mission plan; load index sensitivity; clustering algorithm

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Citation: Yan, Y.; Sun, Z.; Hou, Y.; Zhang, B.; Yuan, Z.; Zhang, G.; Wang, B.; Ma, X. UAV Swarm Mission Planning and Load Sensitivity Analysis Based on Clustering and Optimization Algorithms. *Appl. Sci.* **2023**, *13*, 12438. https://doi.org/10.3390/app132212438

Academic Editor: Yutaka Ishibashi

Received: 28 September 2023
Revised: 5 November 2023
Accepted: 7 November 2023
Published: 17 November 2023

1. Introduction

Unmanned Aerial Vehicle (UAV) swarm systems, encompassing an aggregation of drones collaborating in tandem to execute multifaceted tasks, represent an innovation with considerable promise in diverse sectors, including urban logistics, maritime surveillance, border security, and regional search and rescue operations. Especially pertinent to time−critical regional searches with numerous targets, deploying a cost−effective UAV swarm in the specific zone could augment the numerical advantage, thereby expediting the task completion time.

In managing UAV swarms, the control hierarchy is typically divided into four stratified layers: the task assignment layer, the trajectory planning layer, the trajectory tracking layer, and the base control layer. The foremost layer, task assignment, involves designated personnel selecting tasks and issuing task commands. The second layer, the flight path planning layer, employs a designated trajectory planning algorithm to formulate optimal flight paths for either the collective swarm or individual units. The third layer, the trajectory tracking layer, takes the coordinated trajectory as the desired path and uses trajectory tracking control methods to generate attitude guidance commands. The fourth layer comprises the UAV's individual control system, which formulates respective control directives for the rudder surface. Nevertheless, when deploying drone swarms in practical applications faced with specific tasks and an unknown numbers of drones, determining how to optimally allocate drones based on mission timelines, coverage requirements, and matching optimal platforms and payload capacities to enhance the efficiency of the drone swarm remains a research−worthy challenge.

The existing literature predominantly assumes the number and payload capacity of UAVs as known variables. These studies often involve only a few drones, not addressing the task scheduling for large−scale drone swarms, and seldom delve into the analysis of task payload suitability. Addressing this gap necessitates the consideration of two pivotal factors. From the perspective of matching swarm size, the number and routes of the drones need to be as optimal as possible to meet the task requirements. From the viewpoint of matching payload indicators, taking an electro–optical payload as an example, it is essential to jointly verify the impact of drone performance and electro–optical payload capabilities on task requirements [1–6]. Through scrutinizing UAV swarm task planning, we aim not only to formulate algorithms for superior task planning, but also to evaluate the interaction between UAV platforms and payload performances on overall mission effectiveness. This analytical approach facilitates the validation of the feasibility and efficacy of designated indices. This nuanced approach thereby enhances UAV swarm task−planning optimization, taking into account UAV numbers and routes, as well as the aptitude of mission loads.

Two prevalent strategies are generally adopted to solve the problem of UAV swarm task assignment and track planning. The first employs optimization algorithms to transmute the issue into either an offline or online optimization challenge, premised on constraints such as time, energy, or obstacle avoidance, given a known UAV quantity and unknown targets [7–9]. For example, Carabaza (2017) studied the UAV track planning problem under the minimum search time target based on the ant colony optimization method [10]. Yuan (2021) studied the problem of optimal communication relay for UAV clusters based on ant colony and clustering methods [11]. Commonly used optimization algorithms include the particle swarm optimization algorithm, crow search optimization algorithm, and more advanced gray wolf optimization algorithm, artificial hummingbird optimization algorithm and Harris Eagle optimization algorithm, etc. These algorithms have solved many practical problems in the engineering field and achieved good results [12–14]. An alternative approach leverages reinforcement learning to cultivate UAV swarms with autonomous decision−making capabilities, enabling real−time task objective assignment and flight path planning. Kaufmann (2023), based on image recognition and reinforcement learning algorithms, studies the path assignment of UAVs using visual navigation, and beats human champions in an FPV test [15]. Hu (2022) studied the real−time planning problem of UAV tracking dynamic targets in a large−scale unknown environment using the deep reinforcement learning method [16].

Regarding the verification and matching of drone platform performance and electro–optical payload indicator performance, they are typically decoupled from platform design and task requirements. From task planning to drone design, payloads are often considered optional accessories, making it challenging to achieve optimal metrics based on swarm tasks. Currently, only some studies comprehensively verify the relationship between electro–optical payloads, drone performance, and task requirements. Generally, these investigations are based on optimization concepts, modeling the payload capability−task requirements, and seeking optimal metrics under objectives such as timeliness and energy consumption [17,18]. Gustavo (2015) calculated the camera's coverage width, factoring in the field width of the optical sensor, the camera lens' focal length, and the distance between the camera and the ground, subsequently crafting an area coverage path that minimizes task time [19]. Carmelo (2016) designed an overlay path−planning algorithm with the objective of low energy consumption, grounded on an actual energy model and image resolution constraints, additionally proposing two energy−conscious safety mechanisms for returning home [20]. Wang (2022) formulated a multi−objective mathematical model aiming to minimize both flight path length and correction frequency, considering the path−tracking deviation and turning radius of UAVs during offshore platform patrols while introducing a UAV path planning strategy rooted in genetic algorithm principles [21]. Targeting UAV search and rescue operations, Jing (2023) investigated area coverage search techniques and task parameter configurations under the influence of sector scanning photoelectric load, comparing the efficacy of different optimization algorithms in the search and rescue frameworks involving sector photoelectric devices [22].

These aforementioned studies have actively examined the intricacies of UAV swarm task planning, yielding fruitful results. However, their primary emphasis has been on scenarios featuring a predetermined count of UAVs, neglecting critical variables such as drones' quantity and payload capacities. In real−world applications, the imperative lies in ascertaining the optimal drone count for deployment and effectively allocating target routes for each drone, especially in situations involving time−intensive and multifaceted missions.

The key contributions of this paper can be summarized as follows:

- In contrast to traditional task−planning frameworks, this study establishes a unified framework for UAV swarm search task−planning and payload performance optimization. On the two−dimensional level, it mainly conducts optimal task scheduling and outputs a two−dimensional projection of the three−dimensional trajectory. Building upon this, considering drone performance and electro–optical payload performance, the problem is elevated to three dimensions. A thorough examination is conducted on how these performance indicators impact task completion capability, providing results from optimal index analysis.
- An improved cluster algorithm is devised based on target geographic distribution. The inner layer of the algorithm introduces an ant colony optimization algorithm, only considering the optimal trajectory of the entry and search segments. The outer layer of the algorithm retains the optimizer interface, allowing for the optimization of variables such as the clustering circle radius and cluster center location to plan the optimal track of the cluster.
- A task model for UAV swarm search is established. It introduces elements such as the drone platform's ascent and descent angles, the electro–optical payload's visible distance, and the viewing angle. With the task duration as the objective, it conducts sensitivity analysis and optimization of performance indicators.

The organization of this paper is as follows: Section 2 formulates the problem of UAV swarm search. Section 3 introduces the cooperative search task−planning algorithm for UAV swarms. Section 4 offers an analysis through modeling and simulation to validate the efficacy of the proposed algorithm. Lastly, Section 5 presents the conclusion and outlines avenues for future research.

2. Description of Problem

2.1. Mission Scenario

To investigate the complexities of UAV mission planning, this study develops a simulation for the expedited search operations conducted by a UAV cluster (Figure 1). Within the designated mission area, 100 target points are randomly generated, represented by green points in Figure 2. The drone swarm gathers from multiple points outside the mission area, corresponding to the red points in the picture. Once the mission directive is issued, the drone swarm, equipped with electro–optical payloads, departs from the gathering point and conducts a quick search and filming for each target. Regarding the photoelectric payload of the UAVs, the visual range at each target point manifests as a spherical cone, wherein the apex of the cone and the sphere's center align perfectly. As the UAV approaches the target from its cruising altitude, it swiftly intersects the upper circular edge of this spherical cone, transitioning to horizontal flight, enabling it to spot the target and maintain level flight. Upon reaching this upper circular boundary, the UAV alters its course towards the next target, maintaining level flight. Once this boundary is again reached, the UAV initiates an ascent, rapidly returning to cruising altitude before proceeding to the subsequent target. If the proximity to the subsequent target does not permit ascent to cruising altitude, the UAV preemptively transitions into a descent to facilitate efficient target engagement.

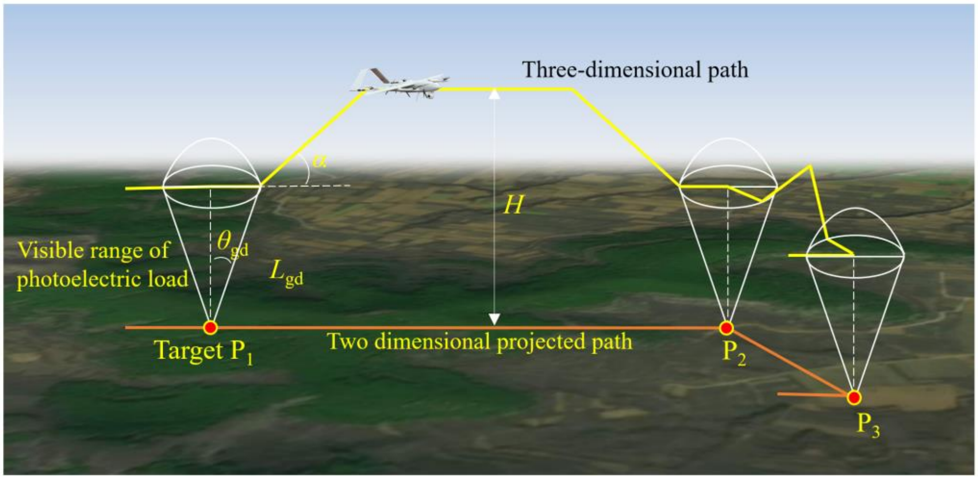

Figure 1. Mission scenario.

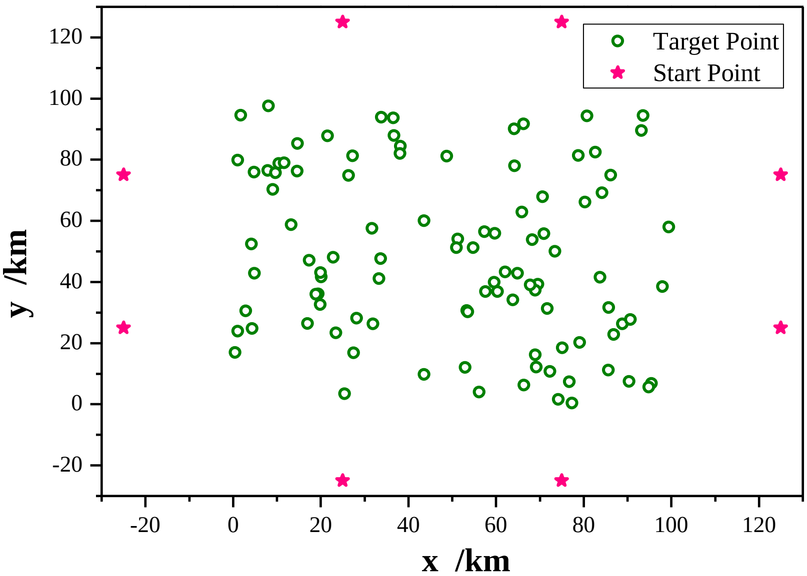

Figure 2. Target points and start points.

In this task, the UAV swarm initiates its operation from the starting point, maintaining a consistent speed of 100 km/h and a cruising altitude of H = 3 km. As it approaches the vicinity of a target point, it transitions into a descent trajectory, eventually stabilizing at a lower altitude to facilitate level flight. Concurrently, the UAV swarm executes close−range imaging of the target point. After the shooting is completed, they ascend and re−enter cruising altitude until they approach the next target and then descend again, thus perpetuating this cyclic process throughout the mission duration.

2.2. Assumption

In the scenario, the following assumptions are introduced:

1. All UAVs commence their mission simultaneously, maintaining a constant speed throughout the operation. They are designed to avoid collisions, have a sufficiently small turning radius, and the maximum range meets the requirements;
2. The visible range of the drone's electro–optical payload is equivalent to a cone. Each target entering the drone's visual cone is judged as being seen. After leaving the visual cone, it is judged as the search completed.

2.3. Mission Evaluation Function

In the section concerning two−dimensional goal allocation, an optimization algorithm is implemented to refine task requirements, and the objective function is G_1. G_1 is formulated as outlined below:

$$G_1 = \min : w_1 * N + w_2 * L_1 + w_3 * L_2 + w_4 * \sigma_1$$
$$\begin{cases} L_1 = \frac{1}{N}\sum L_i \\ L_2 = \max : \{L_i\} \\ \sigma_1 = \sqrt{\frac{1}{N}\sum (L_i - L_1)^2} \end{cases} \tag{1}$$

where N denotes the number of drones, L_i signifies the path length of each unit within the cluster, with i = 1, 2, . . ., N; σ_1 represents the standard deviation of the path length for each unit in the cluster, and w_1, w_2, w_3, and w_4 are weighting coefficients adaptable to various task requirements.

During the 3D track optimization phase, an optimization algorithm is used. Based on the multi−objective distribution of the swarm and the two−dimensional optimized trajectory obtained earlier, the task time is calculated, and optimization analysis is conducted on three indicators. The form of the optimization objective function is G_2. G_2 is represented below:

$$G_2 = \min : \ w_5 * T_1 + w_6 * T_2$$
$$\begin{cases} T_1 = \frac{1}{N}\sum T_i \\ T_2 = \max : \{T_i\} \end{cases} \tag{2}$$

Ti represents the time allocated for the search task for each unit within the cluster, with w_5 and w_6 acting as the weighting coefficients. The parameters under optimization include the UAV's climbing and descending angles α, the discernible distance of the photoelectric load L_{gd}, and the observable angle of the photoelectric load θ_{gd}.

3. Methods

3.1. Improved Cluster Algorithm Based on the Geographic Distribution of the Target

In the initial algorithm development segment, the focus is primarily on allocating the number of drones and the optimal path for each drone within the cluster. The research is based on optimization algorithms and clustering algorithms. The entire algorithm consists of three main components, namely, sequential clustering algorithm, single−drone optimal trajectory algorithm, and cluster mission planning optimization algorithm.

The clustering algorithm functions as a classification mechanism to group seemingly disordered target points, ensuring that the target points within the same group are close in position. This organization ensures that the target points within the same group are proximal to each other, reducing long−distance transfers for a single drone while keeping the target points of different groups as far apart as possible. At the same time, it avoids overlapping areas for drones, preventing resource wastage.

Traditionally, k−means clustering algorithm represents classical clustering algorithms. At its core, it partitions data into 'k' groups, with 'k' entities randomly selected as the initial clustering centers. Then, the distance between each entity and the respective clustering centers is calculated to assign each entity to the nearest cluster center. Although this method boasts a high exploratory potential, it is typically marred by a considerable degree of uncertainty and extensive iterative computing time costs. Given the introduction of multiple optimizations in the proposed algorithm, the initial calculation stages strive to diminish uncertainty within the optimization process. This approach aims to yield results that are not only interpretable, but also conducive to further optimizations.

To mitigate these challenges, this paper introduces a sequential clustering method that hinges on geographic coordinates, advancing from the traditional clustering approaches (Algorithm 1). During the clustering phase, two pivotal optimization parameters are highlighted: the cluster circle diameter D and the cluster circle positioning distance Δd.

The former parameter, D, signifies the cluster circle's diameter, influencing the cluster count and the number of clustered target parcels. Conversely, Δd denotes the minimum positional shift between the starting point of a new cluster and the center of the preceding cluster during a cluster transition. This parameter influences the relative positioning amongst the cluster circles to adjust the relative position between the cluster circles, thereby improving the uniformity of clustering in densely targeted areas and reducing the spatial overlap of clusters. In the sequential clustering process, each cluster's target points, which correlate to the tasks assigned to each drone, need to be traversed. This problem is akin to the classic *TSP* in mathematics. It dictates that each drone tasked with visiting 'n' target points must define a path encompassing all designated points, with the stipulation that each target is visited only once before returning to the initial starting position. This path selection aims to minimize the overall journey length amongst all potential paths. Recognized as a quintessential combinatorial optimization issue, *TSP* falls under the category of $NP-$complete problems. As of now, no flawless solution has been identified.

In this paper, the ant colony optimization (ACO) algorithm is employed to solve the shortest path problem for drones, approximating the optimal solution. The basic principle of the ACO algorithm is derived from nature's shortest path principle for foraging. According to entomologists, ants can find the shortest path from food sources to their nests without any hints, even in complex environments (Figure 3).

Algorithm 1. Improved cluster algorithm based on the geographic distribution of the target

1. The coordinates of the target point set $\{P_{tar}\}$, the assembly point coordinate $\{P_{jjd}\}$, and the reference point coordinate P_0;
2. Initialize parameters;
3. Determine the nearest point P_{ini-i} closest to P_0, and the distance between P_{ini-i} and center C of any cluster circle is $\geq \Delta d$;
4. Starting with P_{ini-i}, find the farthest point P_{far-i} within the distance D;
5. The coordinate C_i of cluster circle center is determine as $d\ C_i = \frac{P_{ini\text{-}i}+P_{far\text{-}i}}{2}$;
6. Search by distance and record point set $\{P_{ci,j}\}$, within the diameter D, centered on C_i;
7. Add the assembly point $P_{jjd,j}$ closest to C_i in $\{P_{ci,j}\}$;
8. Eliminate $\{P_{ci,j}\}$ in $\{P_{tar}\}$;
9. Initialize pheromones and ants within $\{P_{ci,j}\}$;
10. Randomly initialize the solution space of the problem;
11. Initialize the pheromone value for each solution;
12. Create a group of ants and place them on different solutions;
13. Iteratively update pheromones and ant paths;
14. Carry out the following for each ant;
15. Choose the next solution according to the pheromone and heuristic information;
16. Update ant's path reconciliation;
17. Update the pheromone along the ant's path;
18. Carry this out for all ants;
19. Update the global optimal solution;
20. Update the global optimal solution based on the solution of all ants;
21. Update pheromone;
22. Record the path information $\{Tour_i\}$ within $\{P_{tar}\}$;
23. Iterate until $\{P_{tar}\}$ is empty, and all points are traversed;
24. Update the pheromone matrix according to the pheromone along the ant path;
25. End condition judgment;
26. Terminate the iteration when reaching a predetermined number of iterations or meeting a certain stopping condition.

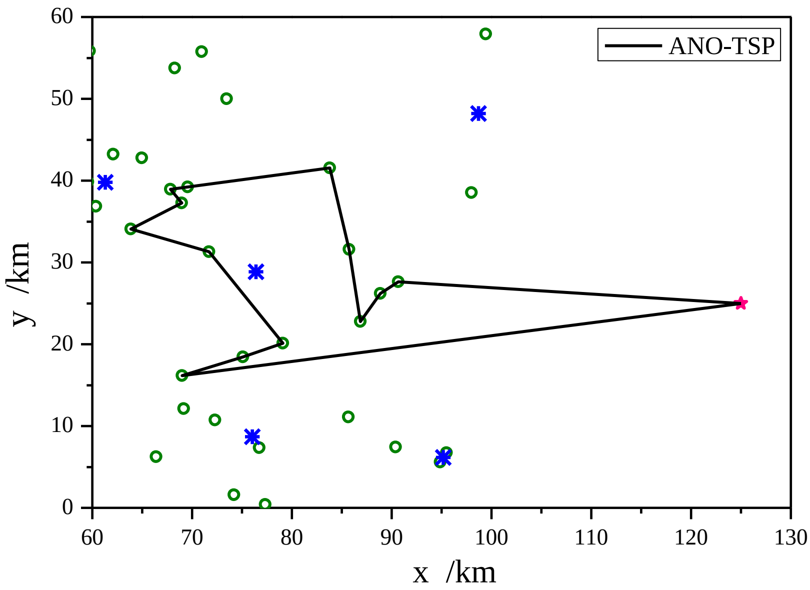

Figure 3. ANO−TSP path plan in cluster. The green circle represents the target, the blue symbol represents the center of clustering, and the pink star represents the start point.

3.2. Optimization Algorithm

To interpret the optimization results and prevent the problem of local optima due to a single algorithm, this paper utilizes both the particle swarm optimization (PSO) and crow search optimization (CSO) algorithms concurrently to optimize the objective function.

The particle swarm optimization (PSO) is an optimization algorithm inspired by biomimicry principles that emulates the collaborative behavior observed in bird flocks or fish schools to identify the optimum solution to a problem. This algorithm operates with a set of entities called particles. Each particle represents a potential solution in the solution space. These particles iteratively adjust their positions and velocities to find the best solution.

The crow search optimization (CSO) is a heuristic optimization method based on bird behavior, simulating the crows' strategized foraging activities to ascertain the optimal solution. The foundational idea behind the CSO is to perceive the problem awaiting optimization as a search space, with the positions within this space representing potential solutions since crows optimize the quality of solutions through cooperative and competitive behaviors.

In the optimization methodology adopted in this study, the PSO algorithm is implemented with a population of 40 particles undergoing a maximum of 100 iterations. The learning factors are fixed at 1.5 for both components, complemented with maximum and minimum inertial weights of 0.8 and 0.4, respectively. Meanwhile, the CSO algorithm has a population of 40 crows, a maximum iteration cycle of 100, a flight distance parameter of 2, and an exploration probability of 0.2.

3.3. Sobol Sensitivity Analysis

To simplify the intricacies of the problem at hand, this analysis centers on three crucial parameters: the UAV's climbing and descending angle α, the angular photoelectric load's viewing distance L_{gd}, and its viewing angle θ_{gd}. While these parameters function independently, they collectively shape the 3D search path of the UAV, influencing the cluster's task completion time. Considering the large−scale demonstration of performance indicators, a sensitivity analysis method is warranted to analyze these indicators comprehensively. Thus, the Sobol sensitivity analysis method is chosen for this purpose. Suppose that the input–output relationship of the structural system under consideration can be determined by

$$Y = g(X), X = (X_1, X_2, \ldots X_n) \tag{3}$$

The global sensitivity index and the principal contribution sensitivity index based on variance can be obtained as

$$S_i = \frac{Var[E(Y|X_i]}{Var(Y)}$$
$$S_i{}^T = 1 - \frac{Var[E(Y|X_{-i}]}{Var(Y)} \tag{4}$$

4. Results

4.1. Simulation Steps and Conditions

Before optimization, validation tests were conducted using varying parameters: cluster diameter D = 30 km, cluster circle positioning spacing Δd = 0 km and D = 40 km, and cluster Δd = 5 km. The optimal path was identified using sequential clustering and ant colony optimization algorithms. This path length was measured from the UAV's starting point to each aircraft's designated final target. The results are graphically illustrated in the accompanying Figures 3 and 4 and Table 1.

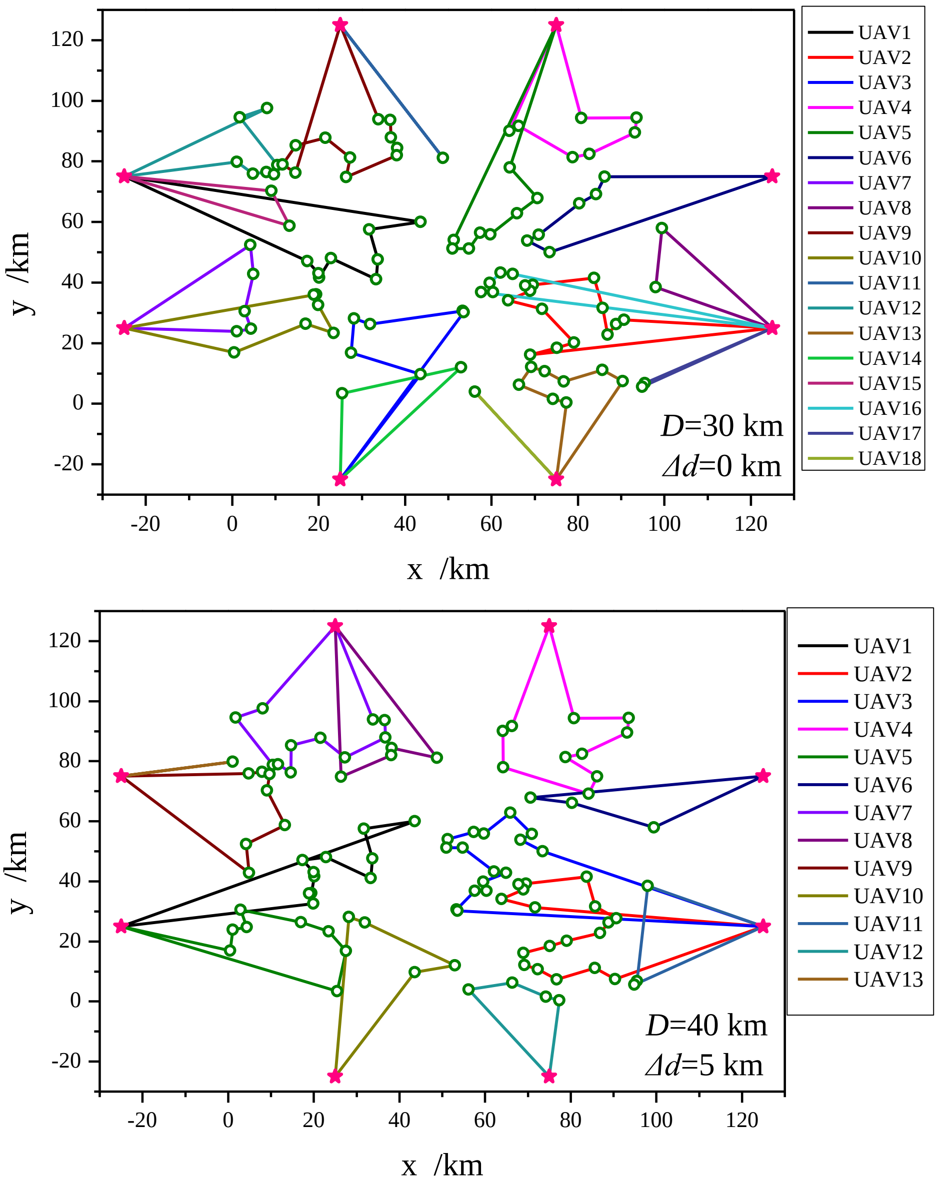

Figure 4. UAVs' path plan before optimization. The green circle represents the target, and the pink star represents the start point.

Table 1. Relevant data of UAVs' path plan before optimization.

[D, Δd]	N	**Mean**$\{L_i\}$	**Max**$\{L_i\}$	σ_1
[30, 0]	18	70.50	116.53	23.58
[40, 5]	13	86.55	141.87	33.97

For the scenario where D = 30 km, Δd = 0 km, a total of 18 UAVs are required to search 100 targets in a cluster formation. In this configuration, the longest path ranged from 34.52 km to 116.53 km, with an average of 70.50 km and a standard deviation of 23.58 km. When D = 40 km and Δd = 5 km, the mission necessitates 13 UAVs to search the same number of targets collectively. In this setup, the path lengths vary between 26.49 km and 141.87 km, averaging 86.55 km and a standard deviation of 33.97 km. The data show that the chosen values for cluster diameter D and cluster circle positioning spacing Δd significantly impact the number of UAVs deployed in the cluster and the extent of the longest path, indicating a substantial scope for optimization.

4.2. Optimized Two–Dimensional Object Assignment

For the cluster diameter D, the range is set to [20, 100]. The cluster circle positioning distance Δd spans a range of [0, 50]. The weights w_1, w_2, w_3, and w_4 are set to 1, 0.5, 0.5, and 0.5, respectively. The optimization procedure and its outcomes are shown in Figure 5 and Table 2:

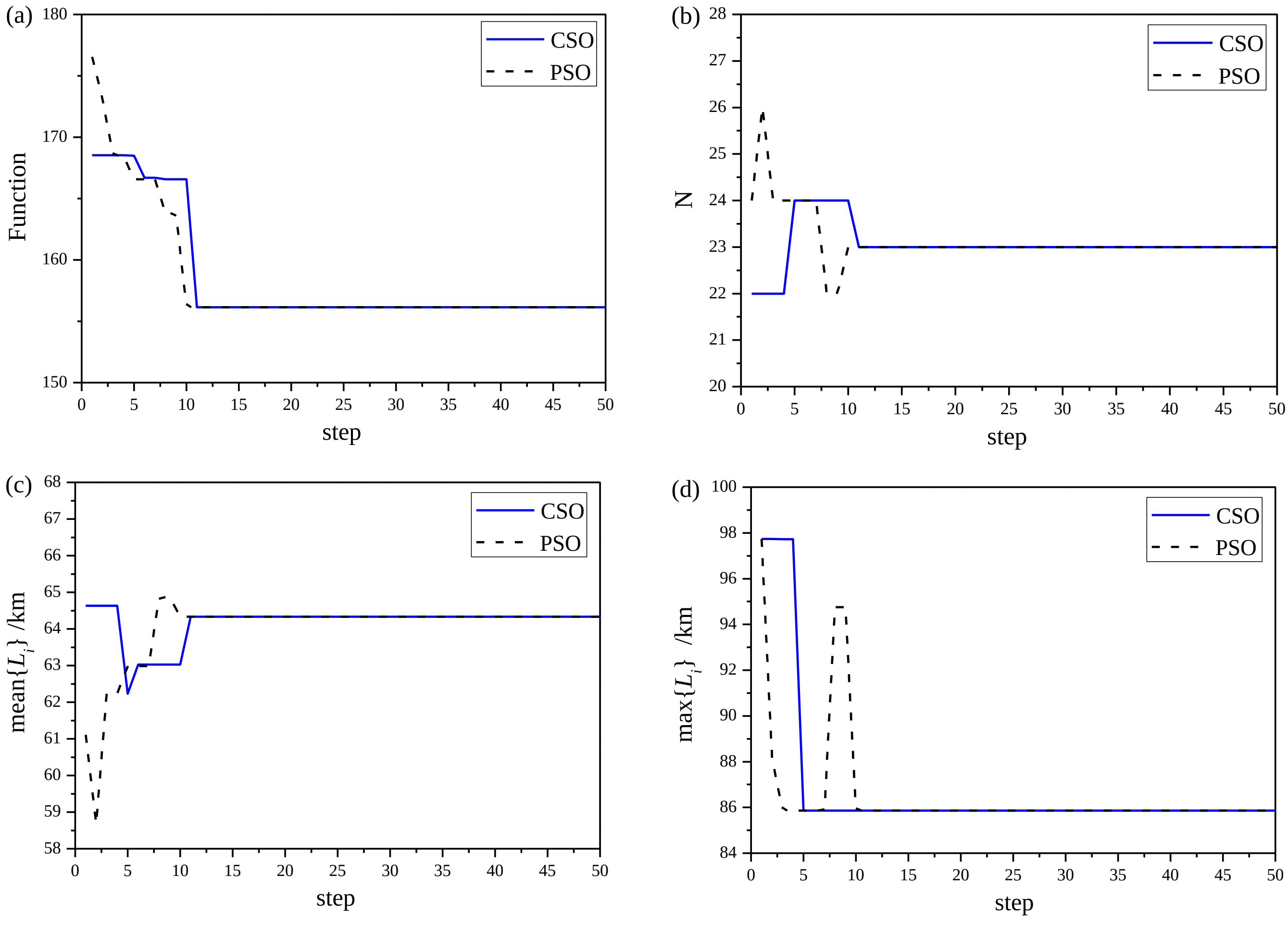

Figure 5. *Cont.*

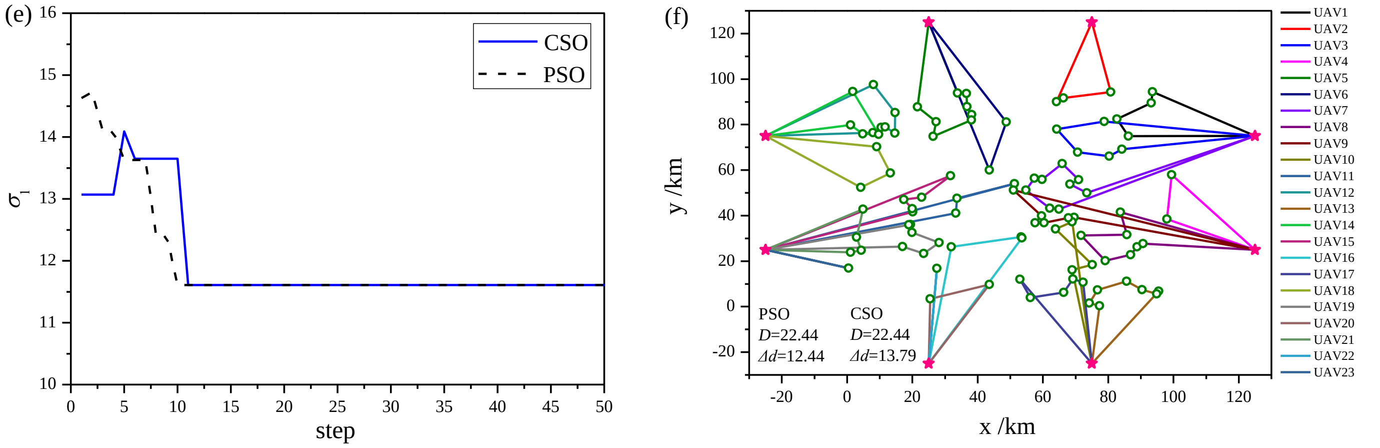

Figure 5. Optimization process. (**a**) Fitness. (**b**) Number of UAVs. (**c**) Mean length. (**d**) Max length. (**e**) Standard deviation. (**f**) Result. The green circle represents the target, and the pink star represents the start point.

Table 2. Relevant data of UAVs' path plan after optimization.

Algorithm	$[D, \Delta d]$	Function	N	Mean$\{L_i\}$	Max$\{L_i\}$	σ_1
PSO	[22.44, 12.44]	156.14	23	64.34	85.86	11.61
SCO	[24.44, 13.79]	156.14	23	64.34	85.86	11.61

The trend analysis shows that both the PSO and CSO methods can achieve convergence swiftly, with the PSO algorithm necessitating fewer iterations to reach convergence. When comparing the fitness, quantity, average path length, most extended path length, and standard deviation of each machine's path length, both methods produce identical results, indicating that the original problem has already converged.

For the initial optimization task, 23 unmanned aerial vehicles can accomplish a multi−objective search in the shortest approximate time. Using both optimization methods, the paths obtained for each machine are the same, proving that the solution to the original problem obtained using this algorithm is highly stable and is minimally affected by the algorithm itself. In addition, in the optimization results obtained from both methods, the values corresponding to the optimal cluster diameter are nearly identical, and the disparities in the cluster migration distances are inconsequential, resulting in no significant differences in the final outcomes, indicating that the original algorithm has a certain tolerance for the excessively large cluster migration distance.

4.3. Performance Index Analysis of UAV Platform and Electro–Optical Payload

This section uses Sobol sensitivity analysis to access the mission time sensitivity relative to three specific indices. The defined ranges for the UAV climbing and descending angle α, the photoelectric load viewing distance L_{gd}, and the photoelectric load viewing angle θ_{gd} are set to [0, 45] (°), [1, 3] (km), and [0, 60] (°), respectively, with the parameter sample space established at 10,000. The results are presented in Figure 6.

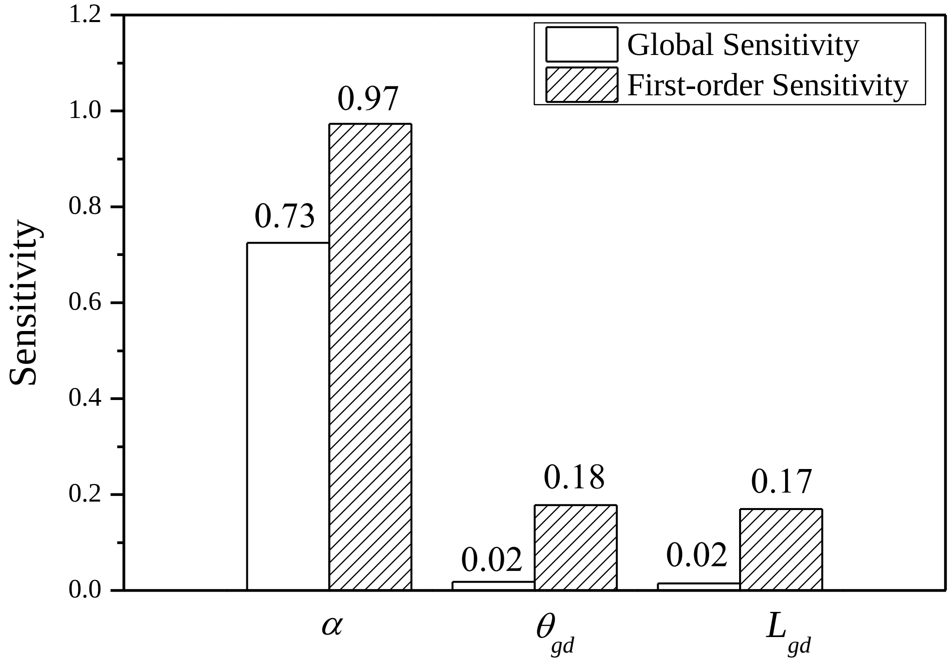

Figure 6. Sensitive analysis result.

From the analysis results, the UAV's climb and descent angle α exhibits a global sensitivity and first−order sensitivity of 0.73 and 0.97, respectively. It has the most direct impact on the task time. On the other hand, the global sensitivity and first−order sensitivity of the photoelectric payload visible distance L_{gd} and the photoelectric payload visible angle θ_{gd} 0.02 and 0.18 and 0.02 and 0.17, respectively. While their impact on task time is comparatively small, it cannot be ignored. They should be considered during metric optimization verification.

4.4. Optimization of the Platform and Photoelectric Load Index

In terms of the trend, both strategies can converge rapidly (Figure 7). However, comparing the results of both methods, the optimization result of the PSO algorithm, near the starting interval of the variable, falls into a local optimum, with the eventual longest task time being 64.75 min (Table 3). In contrast, the CSO algorithm showcases stronger exploratory capabilities, achieving marginally superior results with an optimum task time of 64.39 min.

Table 3. Relevant data of UAVs' platform and photoelectric load index after optimization.

Algorithm	$[\alpha, \theta_{gd}, L_{gd}]$	Function	Mean$\{L_i\}$	Max$\{L_i\}$
PSO	[5.00, 10.00, 1.00]	104.63	39.88	64.75
SCO	[17.95, 51.35, 1.01]	103.87	39.58	64.39

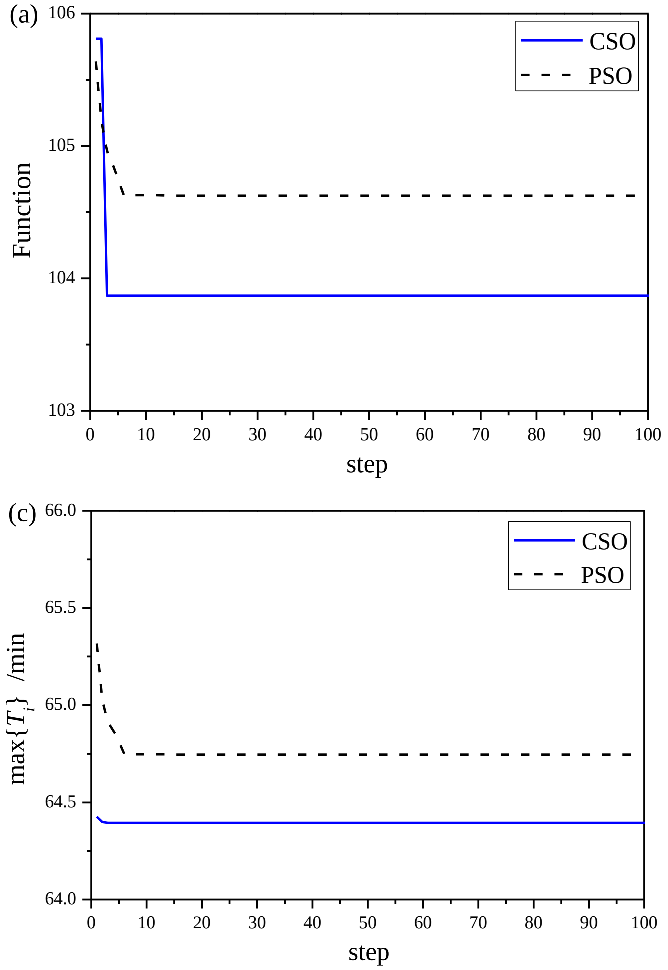

Figure 7. Optimization process. (**a**) Fitness. (**b**) Mean time. (**c**) Max time.

Regarding the photoelectric load's ascent and descent angles, the optimization outcomes from both algorithms align closely, gravitating towards a 1 km interval, indicating that for such a task, the criteria for the photoelectric payload need to be manageable, and meeting the basic requirements will suffice. Concerning the UAV's climb and descent angles, both algorithms optimize the indices to remain below 20°, which illustrates that, within this scenario, the UAV is not anticipated to engage in rapid ascents or descents. When flying in the mission area, they maintain agility in the pitch direction and take the shortest mission route. Concerning the visible angle of photoelectricity, the indicators optimized by both differ significantly. This may be related to the coupling of the aircraft's ascent and descent angles. In practical applications, this can be validated based on a more precise task model.

5. Conclusions

This paper explores the research of task planning and platform–payload metric matching in rapid cluster search. We established a cluster search task−planning algorithm framework, combining an improved sequential clustering algorithm, ant colony algorithm, particle swarm optimization algorithm, and crow search optimization algorithm. This offers a novel approach to addressing the issue. The findings from this paper could serve as valuable references for cluster command and coordination personnel and those involved in platform–load demonstrations.

However, this paper exhibits several shortcomings. From a task analysis standpoint, the current targets are two−dimensional and do not consider the effects of terrain and topography. From the search strategy perspective, the UAV swarm's approach within the mission area appears relatively basic. From the search strategy perspective, the search strategy of the drone cluster in the mission area is relatively simple. When analyzed from the drone platform metrics perspective, the metrics this paper covers are mainly in the pitch direction, and the speed is uniform. However, the real−world task execution by UAVs encompasses many indicators during various phases like glide, climb, mission area level flight, cruise height level flight, and turning process, necessitating a more nuanced and detailed modeling analysis.

Moreover, from the photoelectric metric standpoint, the current modeling of the photoelectric payload is also relatively simple. Real−world applications demand the consideration of other significant factors, including sampling frequency, image resolution, focusing time, and other indicators. Fortunately, the existing deficiencies can be addressed and rectified, building upon the algorithm framework devised in this paper and paving the way for further in−depth research in the future.

Author Contributions: Conceptualization, G.Z. and B.W.; methodology, Y.Y. and Z.Y.; validation, B.Z.; formal analysis, Z.S.; writing—draft, Y.Y.; review and editing, Y.H.; project administration X.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Ying Bi and Pei Ying, the National Natural Science Foundation of China, grant number 12202442 and 12102431.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to regulation of laboratory data management.

Conflicts of Interest: The authors declare no conflict of interest.

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