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A Hierarchical Decoupling Task Planning Method for Multi-UAV Collaborative Multi-Region Coverage with Task Priority Awareness

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Abstract

This study proposes a hierarchical framework with task priority perception for mission planning, to enhance multi-UAV coordination in maritime emergency search and rescue. By establishing a hierarchical decoupling optimization mechanism, the complex multi-region coverage problem is decomposed into two stages: task allocation and path planning. First, a coverage voyage estimation model is constructed based on regional geometric features to provide basic data for subsequent task allocation. Second, an improved multi-objective, multi-population grey wolf optimizer (IM2GWO) is designed to solve the task allocation problem; this integrates adaptive genetic operations and the multi-population coevolutionary mechanism. Finally, a globally optimal coverage path is generated based on the improved dynamic programming (DP). Simulation results indicate that the proposed method effectively reduces total task duration while boosting overall coverage benefits through the aggregation of high-value regions. IM2GWO demonstrates statistically superior performance with respect to the Pareto front distribution index across all test scenarios. Meanwhile, the path planning module based on DP can effectively reduce the overall coverage path cost.



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Keywords: coverage path planning; Multi-UAV task allocation; multi-objective optimization; improved grey wolf optimizer

1. Introduction

Rapidly covering target areas to acquire critical information is crucial in maritime emergency missions [1–3]. Unmanned Aerial Vehicles (UAVs) have become an effective technical means to solve such coverage tasks, thanks to their excellent mobility and flexibility, ease of deployment, and the ability to operate in the air without being restricted by terrain. With the reduction in the cost of UAVs and breakthroughs in swarm cooperative control technology, the cooperative operation of multiple UAVs can effectively improve the cost-effectiveness of the mission and is an ideal choice for multi-area coverage [4].

In actual search and rescue scenarios, there are usually multiple potential regions of interest (ROIs) that are discretely distributed spatially [5]. In research [6–8], this problem is regarded as a combination of the Traveling Salesman Problem (TSP) and the Coverage Path Planning (CPP) problem, being named TSP-CPP. Among these two, the TSP determines the visiting order of multiple ROIs, and the CPP determines the coverage path within the ROI. Chen et al. [9] extends the task scenario to underwater and proposes an underwater vehicle coverage path planning method based on L-SHADE. This method decouples the

original problem into two stages: sub-area coverage path planning and optimal target area sequencing. Tsai et al. [10] proposed the TSP model with the goal of minimizing the task completion time. A heuristic algorithm was proposed to obtain an approximate optimal solution for the multi-region visit order. Jensen-Nau et al. [11] incorporated energy constraints into the algorithm design framework, and an optimized path generation algorithm based on the Voronoi diagram was proposed, which effectively balanced the relationship between regional coverage efficiency and energy consumption. Existing studies usually simplify the surface area into target points for planning. This approach does not consider the influence of the geometric shape characteristics of the area on the coverage path points. It should be particularly noted that there is a significant coupling relationship between the selection of the entrance and exit positions of the UAV in each target area and the planning of the access order [12]. The above method's simplified processing makes it difficult to obtain the global optimal solution and can only achieve approximately optimal coverage.

Multi-UAV collaborative coverage scenarios exacerbate problem complexity, necessitating a task allocation mechanism for load balancing. Xie et al. [13] proposed an extended problem called MTSP-CPP and presented a two-stage heuristic solution method: genetic algorithm-based sub-area allocation and greedy algorithm-based multi-region path planning. Chen et al. [14] calculated the length of the coverage path by constructing a MILP model, conducted task allocation with the minimum time consumption ratio as the evaluation index, and optimized the coverage path using the dynamic programming method. However, as the problem scale increases, the solution efficiency of traditional methods decreases significantly. Intelligent computing methods are applied to solve this problem. Shao et al. [15] employed a dual coevolution algorithm to jointly optimize the intra-area coverage path and inter-area transition paths. Xiao et al. [16] proposed a distributed dynamic coverage approach via discrete soft Actor-Critic (SAC) for enhanced efficiency in complex environments. Zhang et al. [17] proposed an online adaptive CPP method based on the Herd-Foraging algorithm, enabling swarm robots to perform coverage monitoring in unbounded environments.

Although the task planning method driven by intelligent optimization algorithms has improved coverage efficiency, existing studies only focus on the single objective optimization problem of minimizing the voyage cost or energy consumption, lacking a response mechanism for the priorities of different ROIs [18–20]. In time-sensitive mission scenarios such as maritime emergency search and rescue, the ROI exhibits non-uniform priority distribution characteristics [21]. By constructing a value-based coverage sequence optimization model and preferentially detecting high-value areas, the marginal benefit of search efficiency can be maximized [22]. Wang et al. [23] addressed the problem of geological hazard point monitoring by proposing a coverage strategy that prioritizes emergency tasks. This approach ensured that the UAV could access high-priority targets as extensively as possible within a limited time. Hong et al. [24] accounted for regional variations in target existence probability and optimized the search sequence using a genetic algorithm. Separately, Jin et al. [25] addressed the search and rescue problem by establishing target priority as a hard constraint to optimize path length, navigation time, and yaw energy consumption.

This paper considers the target priority index in the regional coverage problem for the first time and proposes a new task planning problem. A multi-UAV collaborative coverage task planning model is constructed with the goals of maximizing the regional coverage benefit and minimizing the UAV task execution time. The decision variables involve multi-region allocation, the access order of multiple regions, and the coverage path, which belongs to a complex multi-constraint, multi-objective task planning problem.

In response to the above problems, this study proposes a hierarchical decoupling optimization framework aimed at improving the coverage efficiency and path economy of multiple UAVs in complex maritime search and rescue missions. First, a geometric aware coverage voyage estimation model is used to accurately quantify the UAV's coverage operation ability. Second, an improved multi-objective, multi-population grey wolf algorithm (IM2GWO) is employed for target area allocation to realize dynamic task planning for multi-area coverage. Finally, an improved dynamic programming (DP) method is used to generate the coverage path and optimize the full coverage trajectory of multiple areas. By decoupling the complex multi-area coverage problem, this framework can systematically reduce the overall coverage path cost and provide an efficient UAV collaborative solution for maritime emergency responses.

The main contributions of this paper are as follows:

- A priority-aware mission planning model that integrates regional value weights and task constraints is constructed. It concurrently optimizes task duration and coverage benefits, prioritizing high-value region responses with coordinated UAV load balancing.
- It improves the multi-objective grey wolf optimization algorithm by incorporating adaptive genetic operators and a multi-population co-evolution mechanism to break through the bottleneck of multi-objective premature convergence and enhance the distribution of the Pareto front.
- A geometric feature-driven path planning method is established. By constructing an antipodal point coverage pattern set, the multi-region path planning problem is decomposed into a multi-stage decision-making problem. The globally optimal path is generated through improved DP.

The remainder of this paper is organized as follows: Section 2 conducts problem formulation; Section 3 introduces a task allocation method based on IM2GWO; Section 4 proposes a coverage path planning method based on improved DP; Section 5 presents the results of the simulation; Section 6 discusses the conclusion and proposes future research directions.

2. Problem Formulation

2.1. Problem Description

As shown in Figure 1, there are multiple regions of interest (ROIs) distributed in the mission area. Each ROI is a convex polygon, and they do not overlap with each other. Define the set of ROIs as $R = \{r_1, r_2, \dots, r_{N_T}\}$, $N_T \in \mathbb{Z}^+$. Each ROI is assigned an initial priority coefficient w_r . Map the priority coefficient of the ROI to the grayscale value (the larger the gray value, the higher the priority). Positively correlated with its priority, the coverage benefit of each ROI decays exponentially over time. Define the set of UAVs as $U = \{u_1, u_2, \dots, u_{N_U}\}$, $N_U \in \mathbb{Z}^+$. The goal of multi-UAV mission planning is to prioritize higher-priority regions and shorten the overall mission time on the basis of covering all regions. Table 1 summarizes the detailed attributes of UAVs and ROIs and their corresponding symbolic representations.

Based on the above description, the problem is studied under the following assumptions:

- (1) Different ROIs have different task priorities, with 10 levels of priority set. The area coverage benefits increase as the priority rises, and at the same time, this benefit gradually decays as the task execution time elapses.
- (2) All UAVs depart from the depot at a constant cruising speed. After completing the coverage search task, they return to the depot the shortest path. Different UAVs fly at different altitudes to avoid collisions with each other.

- (3) Each ROI will only be assigned to one UAV for coverage. A UAV can conduct serialized reconnaissance of multiple target areas in a certain order.

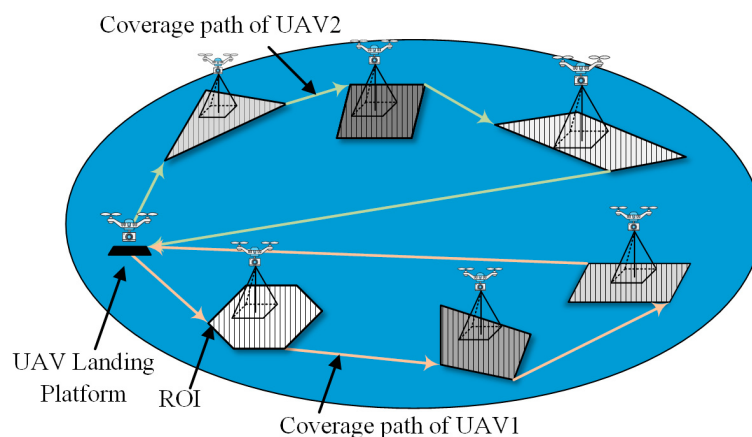


Figure 1. Schematic diagram of multi-UAV, multi-region coverage task scenario.

Table 1. Summary of attributes and corresponding symbols of UAVs and ROIs.

Attributes	Symbols
UAVs	$U = \{u_1, u_2, \dots, u_{N_U}\}$
ROIs	$R = \{r_1, r_2, \dots, r_{N_T}\}$
Number of UAVs	N_U
Flight speed of UAVs	v_d
Yaw angular velocity of UAVs	ω_d
Maximum endurance	$T_{\max}^u$
Number of ROIs	N_T
Coverage time delay of ROI	τ_r^u

2.2. Airborne Sensor Model

Upon arrival at the designated ROI, the UAV activates its photoelectric sensing system for comprehensive area coverage. As illustrated in Figure 2, the sensor's Field of View (FOV) is determined by the UAV's operational altitude combined with the sensor's spatial configuration parameters, including its angular orientation and tilt relative to the aerial platform. This geometric relationship enables precise calculation of ground coverage dimensions and pattern optimization during surveillance operations.

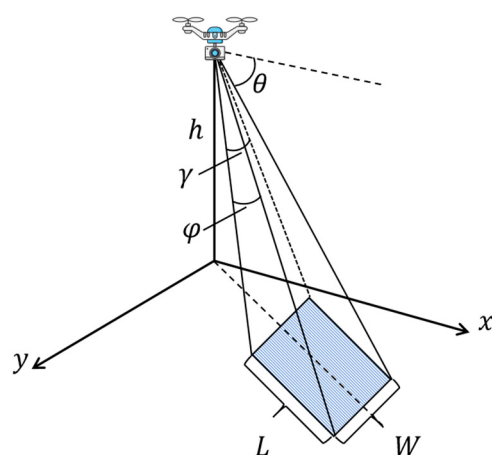


Figure 2. Schematic diagram of sensor FOV.

Given the sea-surface projection area of the FOV is A_{FOV} , the camera to target distance is d_l , where $d_l \approx h$ (camera altitude). The projection area is derived as:

$$A_{FOV} = W \times L \quad (1)$$

where W can be simplified as $W \approx d_l \cdot \gamma$ and L can be simplified as $L \approx d_l \cdot \varphi / \sin \theta$. The range of the camera lens is $\gamma \times \varphi$ and it is determined by the focal length of the camera.

Owing to the minimal distortion and stable performance of fixed-focal-length lenses in aerial imaging, all UAVs are assumed to employ such lenses for visual coverage. Consequently, the θ between the camera and the horizontal plane is set to $\pi/2$.

2.3. Coverage Voyage Estimation Model

For a single target area, Vasquez et al. [26] proposed an optimal back-and-forth path (BFP) coverage planning method based on the rotating calipers algorithm (RCA). The BFP strategy is adopted because it reduces aircraft turns while maintaining image overlap for consistent information registration. As illustrated in Figure 3, the starting and ending positions of the UAV are set at the centroid of the ROI (red star). The RCA generates entry and exit points (red circles) to cover the ROI. Since the BFP sweep direction critically depends on these points, the ROI centroid is designated as both the initial entry and exit location during planning. Subsequently, within-area flight time and transfer flight time are estimated to provide initial parameters for task allocation.

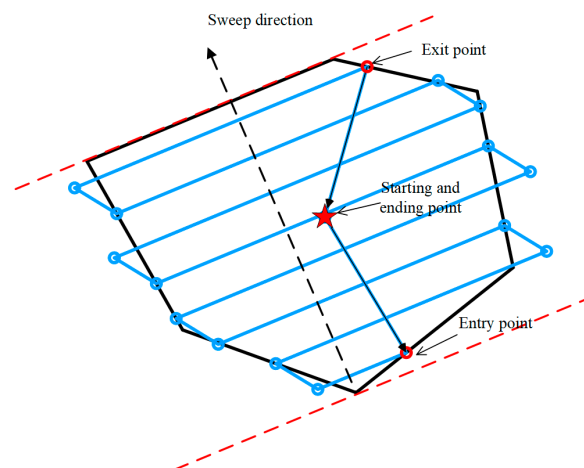


Figure 3. Schematic diagram of single ROI coverage path.

Denote $C_i = \{c_{i,m}\}_{m=1}^{n_i}$, $i \in [N_T] \cup \{0\}$ as the set of coverage path points of r_i . Here, $c_{i,1}$ and c_{i,n_i} represent the entry point and exit point of the ROI, respectively. During trajectory transitions between consecutive waypoints, the UAV undergoes heading angle deflection. Given that the straight flight speed is v_d and the angular velocity is ω_d , let $t_s(r_i)$ represent the expected time for a UAV to cover an ROI:

$$t_s(r_i) = \sum_{m=1}^{n_i-1} \Delta D(c_{i,m}, c_{i,m+1}) / v_d + \sum_{m=1}^{n_i-1} \Delta \Phi(c_{i,m}, c_{i,m+1}) / \omega_d \quad (2)$$

where $\Delta D(\cdot)$ computes inter-point distances and $\Delta \Phi(\cdot)$ determines deflection angles between adjacent path points.

Denote $t_f(i, j)$ as the expected time for the UAV to travel from the r_i to r_j :

$$t_f(r_i, r_j) = \Delta D(c_{i,n_i}, c_{j,1}) / v_d + \Delta \Phi(c_{i,n_i}, c_{j,1}) / \omega_d \quad (3)$$

where c_{i,n_i} represents the exit point of the r_i and $c_{j,1}$ represents the entry point of the r_j .

Assume that the access order of ROI assigned to u_k is $S_{u_k} = \{r_1, \dots, r_m\}$, $m \in N_T$. Then, the starting coverage time for the first ROI is:

$$T_{start}(r_1) = t_f(0, r_1) \quad (4)$$

The ending time for the first ROI is:

$$T_{end}(r_1) = t_f(0, r_1) + t_s(r_1) \quad (5)$$

Similarly, it can be known that the starting coverage time on the second ROI is:

$$T_{start}(r_2) = T_{end}(r_1) + t_f(r_1, r_2) \quad (6)$$

The ending time for the second ROI is:

$$T_{end}(r_2) = t_f(0, r_1) + t_s(r_1) + t_f(r_1, r_2) + t_s(r_2) \quad (7)$$

By analogy, the coverage ending time for r_i ($1 \leq i \leq m$) is:

$$T_{end}(r_i) = t_f(0, r_1) + \sum_{i'=2}^i t_f(r_{i'-1}, r_{i'}) + \sum_{i'=1}^i t_s(r_{i'}) \quad (8)$$

Therefore, for a given access order, the single UAV coverage completion time is:

$$T_{total} = t_f(0, r_1) + \sum_{j=2}^{m-1} t_f(r_{j-1}, r_j) + \sum_{j=1}^m t_s(r_j) + t_f(r_m, 0) \quad (9)$$

Taking the end moment of regional coverage as the reference value of the task delay, the time-weighted coverage benefits of each ROI is calculated as follows:

$$\Gamma_{u,r} = w_r \cdot e^{-\lambda \tau_r^u} \quad (10)$$

where w_r is the initial coverage benefit of each ROI; τ_r^u represents the time delay for the coverage of the ROI; and λ is the attenuation coefficient of the regional coverage benefit.

2.4. Objective Function

This system model yields a multi-objective optimization formulation maximizing area coverage while minimizing mission time. Define the decision variable $x_{i,j}^u \in \{0, 1\}$ to represent that the UAV moves from region r_i to region r_j . The flag variable $y_r \in \{0, 1\}$ indicates whether the ROI is covered. Assume that the maximum endurance time constraint of each UAV is $T_{\max}^u$. The objective function is as follows:

(1) Maximize the time weighted coverage benefit:

$$\text{maximize } J_1 : \sum_{u \in U} \sum_{r \in R} w_r e^{-\lambda \tau_r^u} y_r \quad (11)$$

Transform the objective function J_1 into the following form to convert it into a minimization problem:

$$\text{maximize } J_2 : \left(1 - \frac{\sum_{u \in U} \sum_{r \in R} w_r e^{-\lambda \tau_r^u} y_r}{\sum_{r \in R} w_r} \right) \quad (12)$$

(2) Minimize the UAV maximum task completion time:

$$\text{Minimize } J_3 : T_{\text{mission}} = \max_{u \in U} T_{\text{total}}^u \quad (13)$$

where T_{mission} represents the longest task completion time among multi-UAVs.

Let $F = [f_1, f_2]$, where $f_1 = J_2$ and $f_2 = J_3$. Based on the above analysis, the objective function is shown as follows:

$$\text{Minimize } F = [f_1, f_2] \quad (14)$$

$$\text{s.t. } \sum_{j \in R} x_{0,j}^u \leq 1, \sum_{i \in R} x_{i,0}^u \leq 1, \forall u \in U \quad (15)$$

$$y_r \leq \sum_{u \in U} \sum_{i \in R \cup \{0\}} x_{i,r}^u, \forall r \in R \quad (16)$$

$$\sum_{i \in R \cup \{0\}} x_{i,r}^u = \sum_{j \in R \cup \{0\}} x_{r,j}^u \quad (17)$$

$$T_{\text{total}}^u \leq T_{\text{max}}^u, \forall u \in U \quad (18)$$

$$\sum_{i \in R} \sum_{j \in R} x_{i,j}^u \leq |R_u| - 1, \forall R_u \subseteq |R|, R_u \neq \emptyset \quad (19)$$

Among these, constraint (15) ensures that each UAV departs from the depot and finally returns to the depot. Constraint (16) ensures that each ROI is covered only once and that it is visited by a UAV; Constraint (17) ensures the continuity of the coverage path of the UAV; Constraint (18) guarantees that the total mission time of a single UAV does not exceed its maximum endurance time limit; and Constraint (19) is used to prevent the generation of sub-loops, where R_u represents the set of ROIs assigned to the UAV.

3. Multi-UAV Task Allocation Based on IM2GWO

3.1. Overall Process

Mirjalili et al. [27] proposed the multi-objective grey wolf optimizer (MOGWO), which is an bionic swarm intelligence optimization algorithm. It is specifically designed for the optimization of continuous solution spaces (such as function optimization and parameter tuning). The core of the algorithm relies on continuous vector encoding $\vec{X} \in \mathbb{R}^n$ and position updates based on Euclidean distance. Since the target area allocation of multiple UAVs belongs to the combinatorial optimization problem, and as the solution space is the permutation and combination of access orders, there are obvious differences in solution representation and optimization mechanisms between the two. In addition, previous studies have shown that the search process of MOGWO is dominated by only three optimal solutions, and so is at a disadvantage in global exploration.

In response to the limitations of MOGWO, this study proposes an improved algorithm named IM2GWO. The main improvements of this algorithm are reflected in three aspects:

- (1) Elite individual retention strategy: Implement the elite retention strategy, create an external archive, and conduct targeted maintenance of the global optimal solution set to effectively preserve the genetic information of superior individuals.
- (2) Adaptive genetic operators: Design adaptive genetic operators. Based on the diversity index of the sub-population evolution stage, dynamically adjust the crossover and mutation probabilities, thereby significantly improving the local search efficiency.
- (3) Co-evolutionary mechanism: Construct a multi subgroup distribution model with dynamic interaction characteristics. While ensuring the independent evolution of each sub-population, set the individual migration of sub-populations to be carried out every K iterations to promote co-evolution among multiple sub-populations.

The complete iterative process of the improved algorithm is shown in Figure 4. The specific steps are as follows:

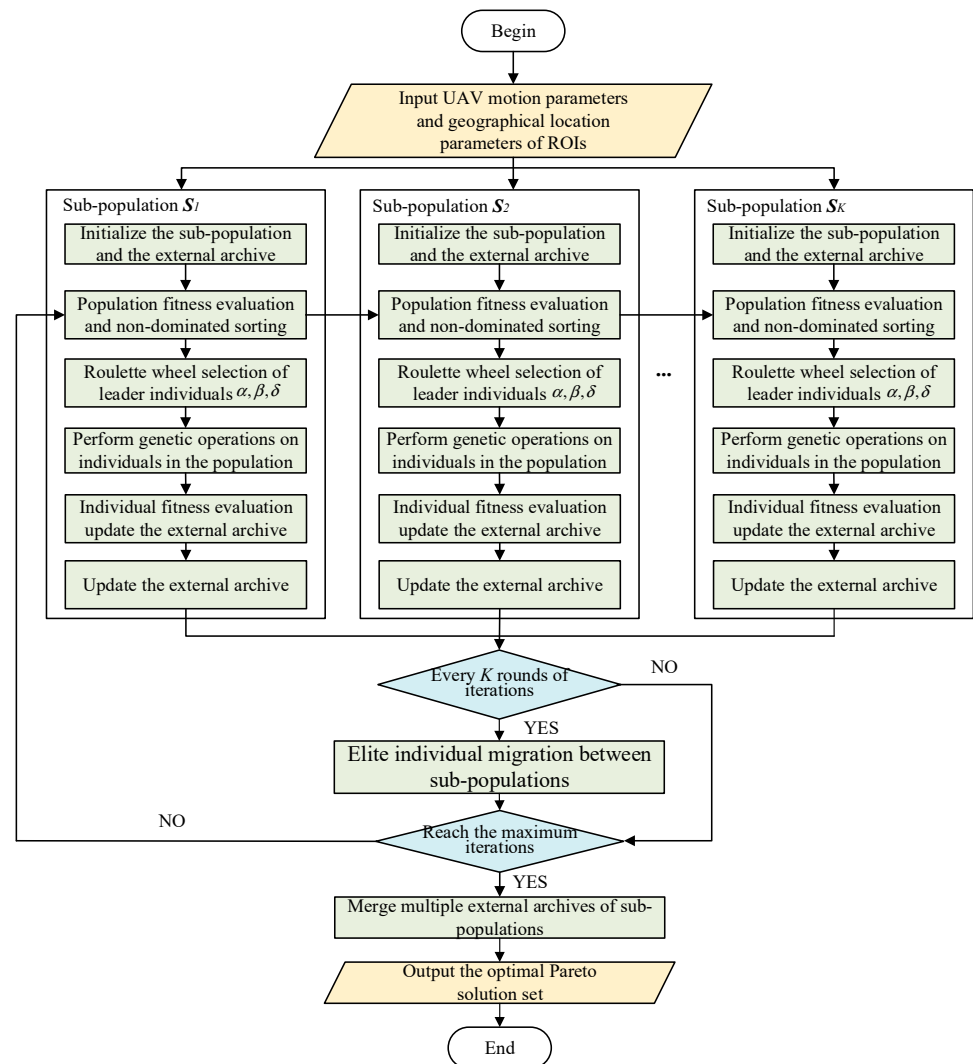


Figure 4. Overall process of the IM2GWO algorithm.

Step 1: Input motion parameters of the multi-UAV and the geographical location information of multiple ROIs;

Step 2: Initialize multiple sub-populations and construct their external archives;

Step 3: Evaluate the fitness of individuals within the sub-populations and perform fast non-dominated sorting, and store the Pareto optimal solution set in the external archive;

Step 4: Calculate the crowding distance of grey wolf individuals in the external archive and sort them. Select the leading wolf individuals through the roulette wheel method;

Step 5: The adaptive genetic operators are used to promote the continuous update of grey wolf individuals within the population, so as to increase the population diversity;

Step 6: Select elite individuals for population migration every K iteration. Repeat steps 2–5 until reaching max iterations;

Step 7: Merge the external archives of multiple sub-populations and output the Pareto optimal solution set.

3.2. Population Initialization and Individual Encoding

The decision variables encompass target area allocation quantities and visitation sequences. To overcome the inefficiency of traditional binary encoding in generating

infeasible solutions, we propose a dual-segment encoding scheme. As illustrated in Figure 5, the left segment encodes target area indices, while the right segment specifies per-UAV allocation counts. This sample encoding corresponds to the following ROI access order: UAV 1: $\{r_1, r_3, r_4\}$, UAV 2: $\{r_6, r_9, r_8\}$, UAV 3: $\{r_5, r_2, r_7, r_{10}\}$.

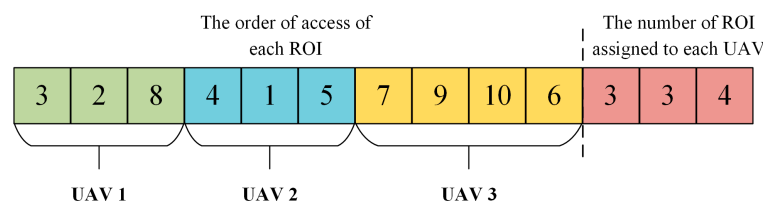


Figure 5. Schematic diagram of individual coding of gray wolves.

Initial solution selection critically influences algorithm convergence. Proximity to the optimum significantly accelerates computational efficacy. Therefore, based on satisfying constraints (15) to (19), a heuristic population initialization method is proposed as follows:

- (1) Partition initialization: Create M sets corresponding to UAVs, randomly assign M distinct ROIs to each set.
- (2) Greedy insertion: Compute pairwise centroid distances between unassigned areas and last-inserted areas in sets. Iteratively assign each unassigned ROI to the set with minimal terminal distance.
- (3) Feasibility enforcement: During iterations, verify path feasibility through task constraints.
- (4) Termination and encoding: Upon full assignment, generate integer encoding representing per-UAV ROI counts.

3.3. Elite Individual Retention Strategy

The original GWO algorithm updates the population by selecting the three optimal individuals to lead the remaining grey wolf individuals. Since the individuals in multi-objective optimization problems cannot be directly compared in terms of superiority or inferiority based on fitness values, it is necessary to find the set of non-dominated solutions in the population through Pareto sorting. To store the non-dominated solutions during the iterative process, an external archive is established to save all non-dominated solutions in each iteration round, and it is updated based on the individual dominance relationship.

The updated method is as follows: For a newly generated solution, if it is dominated by any solution in the external archive, it is rejected from joining; if it dominates some solutions in the external archive, it is added to the external archive, and the dominated solutions are removed; if it has a non-dominated relationship with all solutions in the external archive, the new solution directly enters the external archive. According to the crowding distances of grey wolf individuals in the external archive, the roulette wheel method is used to select the leading wolf from the external archive in each iteration as the α, β, δ wolf individual. The calculation method of the crowding distance is to first perform sorting in ascending order under each objective function, and then calculate according to the following formula:

$$Dis_h = \sum_{j \in O} \begin{cases} Max, & \text{If } h \text{ is at the first or last position} \\ \frac{f_{h+1,j} - f_{h-1,j}}{\max_{h' \in \{1,2,\dots,|p_s|\}} f_{h,j} - \min_{h' \in \{1,2,\dots,|p_s|\}} f_{h,j}}, & \text{otherwise} \end{cases} \quad (20)$$

where Dis_h represents the crowding distance of individual h in the external archive, $h \in \{1, 2, \dots, |p_s|\}$ is the serial number of the sorted individuals, and $|p_s|$ represents the total number of individuals in the external archive; $f_{h+1,j}$ and $f_{h-1,j}$ represent two adjacent

objective function values after sorting under the objective function f_j . $\max_{h' \in \{1, 2, \dots, |p_s|\}} f_{h,j}$ represents the maximum value of individual h among all objective functions, and $\min_{h' \in \{1, 2, \dots, |p_s|\}} f_{h,j}$ represents the minimum value; Max represents a very large positive number.

3.4. Adaptive Genetic Operators

The individual updated method of the original GWO cannot be directly applied to discrete multi-objective optimization problems. Therefore, drawing on the crossover and mutation strategies in the genetic algorithm, genetic search operators are designed to achieve individual updates, which are specifically as follows:

(1) Crossover operator

In each iteration, the selected optimal grey wolf individuals α, β, δ are used as parents to perform crossover operations with other members of the population, guiding the population to evolve towards better solutions. The formula is as follows:

$$X_i(t+1) = \begin{cases} \text{CROSS}[X_i(t), X_\alpha(t)] & \text{rand} \leq 1/3 \\ \text{CROSS}[X_i(t), X_\beta(t)] & \text{rand} \geq 2/3 \\ \text{CROSS}[X_i(t), X_\delta(t)] & \text{otherwise} \end{cases} \quad (21)$$

where $X_i(t)$ represents the current position of individual wolves; $X_\alpha(t)$, $X_\beta(t)$, $X_\delta(t)$ represent the positions of α, β, δ , respectively. Select parent individuals probabilistically through $\text{rand} \in (0, 1]$.

Considering that each ROI can only be assigned to one UAV, to avoid the generation of invalid solutions, a partially matched crossover operator is designed to update the positions of grey wolves. As shown in Figure 6, the start and end positions of parent individual are randomly selected, and the positions of these two groups of genes are exchanged.

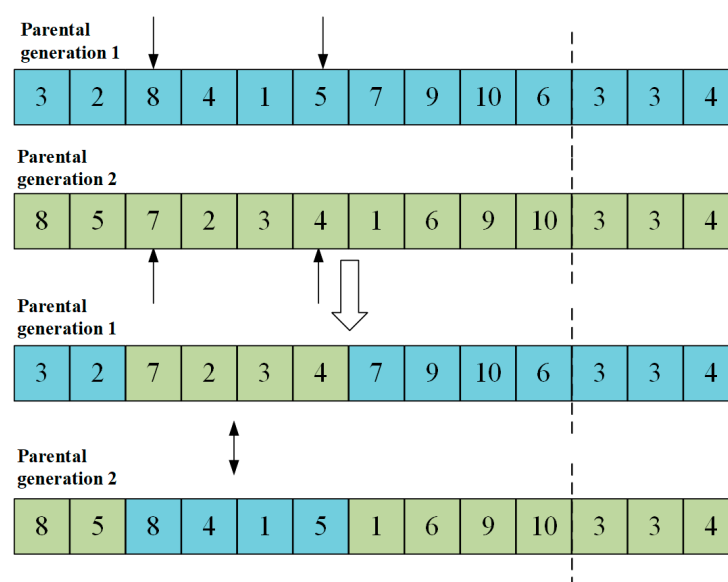


Figure 6. Schematic diagram of partially matched crossover operator.

Establish a mapping relationship based on the exchanged genes, as shown in Figure 7. Taking the mapping relationship of 2–4–5 as an example, it can be seen that there are two Gene 2s in Offspring 1 in the result of the second step. At this time, transform them into Gene 5 through the mapping relationship, and so on until there are no conflicts. Finally, all conflicting genes will go through mapping to ensure that the newly formed pair of

offspring genes has no conflicts. The final generated offspring individual is shown in Figure 8.

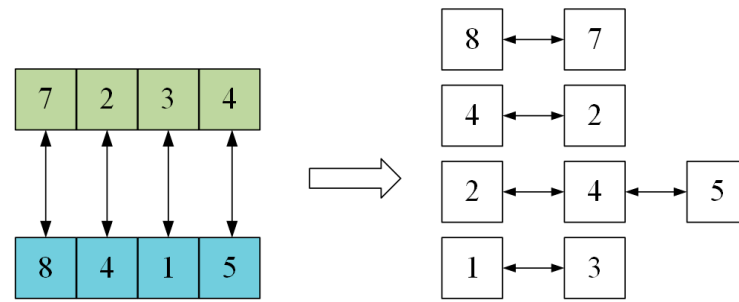


Figure 7. The encoding mapping relationship.

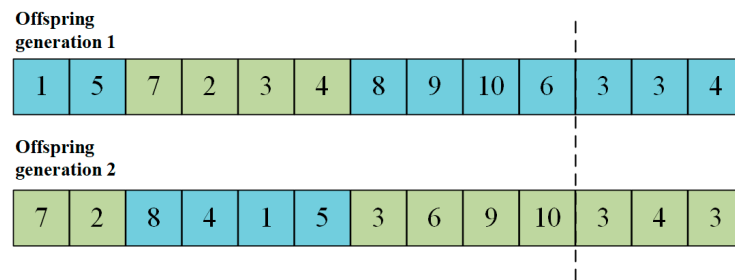


Figure 8. Offspring individuals of crossover operation.

(2) Mutation operator

After updating the individuals using the crossover operator, to accelerate the further convergence of the population towards the optimal solution, a mutation operation is further performed on the offspring individuals. The Hamming distance is a measure of the difference between two binary strings [28]. In this paper, it can be defined as the number of positions where the gene values of two sequences are different at the same position. The purpose is to quantify the difference between an individual and the optimal solution and provide a basis for the hierarchical strategy. Based on the Hamming distance, the difference vectors $d_\alpha, d_\beta, d_\delta$ between the grey wolf individuals and the leading wolves are constructed:

$$\begin{aligned} d_\alpha &= hd(X_i(t), X_\alpha(t)) \\ d_\beta &= hd(X_i(t), X_\beta(t)) \\ d_\delta &= hd(X_i(t), X_\delta(t)) \end{aligned} \quad (22)$$

where X_i represents the coding position of the current individual; $X_\alpha(t)$, $X_\beta(t)$ and $X_\delta(t)$ represent the coding positions of the leader wolf individuals α, β, δ , respectively; and the function $hd(\cdot)$ calculates the Hamming distance between two individuals.

According to the magnitude of the difference vector, select the leader wolf individual as the updated direction of the current individual with probability through random numbers $rand_1$:

$$X'_i(t+1) = \begin{cases} transformation[X_i(t), X_\alpha(t), d_\alpha], & \text{if } rand_1 \leq 1/3 \\ transformation[X_i(t), X_\beta(t), d_\beta], & \text{if } rand_1 \geq 2/3 \\ transformation[X_i(t), X_\delta(t), d_\delta], & \text{otherwise} \end{cases} \quad (23)$$

where $X'_i(t+1)$ represents the new grey wolf individuals generated after multiple mutation operations; $transformation[\cdot]$ represents the number of mutation operations, which is proportional to the size of the difference vector.

Figure 9 shows a schematic diagram of a wolf individual undergoing a mutation operation. According to the magnitude of the difference vector, the swap, insert, and flip operations were performed in sequence. Among these, the swap operator randomly selects two gene loci in the gene sequence; the insert operator intercepts a specified gene segment and repositions it behind the target gene position; and the flip operator performs a reverse recombination operation on the selected gene interval. Based on the above operators, perform the mutation operation on the current grey wolf individual.

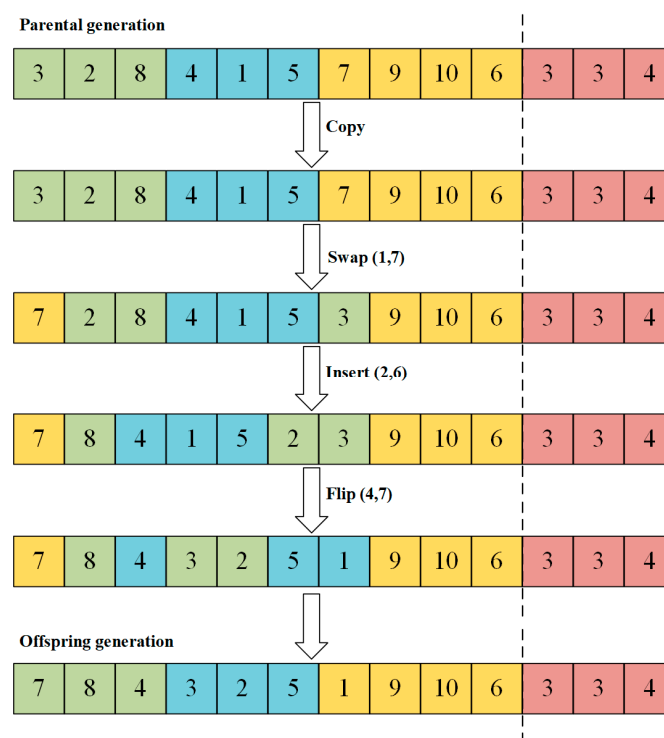


Figure 9. Schematic diagram of triple mutation operation.

Step 1: For each individual in the population (except the leader wolf), calculate the Hamming distance between the gene sequence of this individual and that of the leading wolf.

Step 2: Based on the Hamming distance, calculate the individual mutation intensity and the number of mutation operations.

Step 3: According to the individual mutation intensity, select the usage frequency of three mutation operation operators. When the intensity is high, give priority to more radical operators, such as the flip operator; when the intensity is low, give priority to more conservative operators, such as the swap operator and the insertion operator.

Step 4: Apply the mutated gene sequence to the individual to generate a new grey wolf individual. At the same time, ensure that the mutation operation does not change the sequence length.

3.5. Multi-Subpopulation Coevolution Mechanism

Based on the above genetic operation, a periodic individual migration strategy is introduced to achieve the coevolution of multiple subpopulations. The specific implementation process is shown in Figure 10. It is set that the migration operation is carried out after every K iteration. First, the Pareto front solution set is sorted based on the crowding distance to

generate a migration candidate sequence. On this basis, the high-ranked individuals of the original subpopulation are used to replace the low-ranked individuals of the target subpopulation. The migration operation is executed cyclically until the global population completes the information interaction. This mechanism effectively balances the population diversity and convergence through the directional migration of elite solutions.

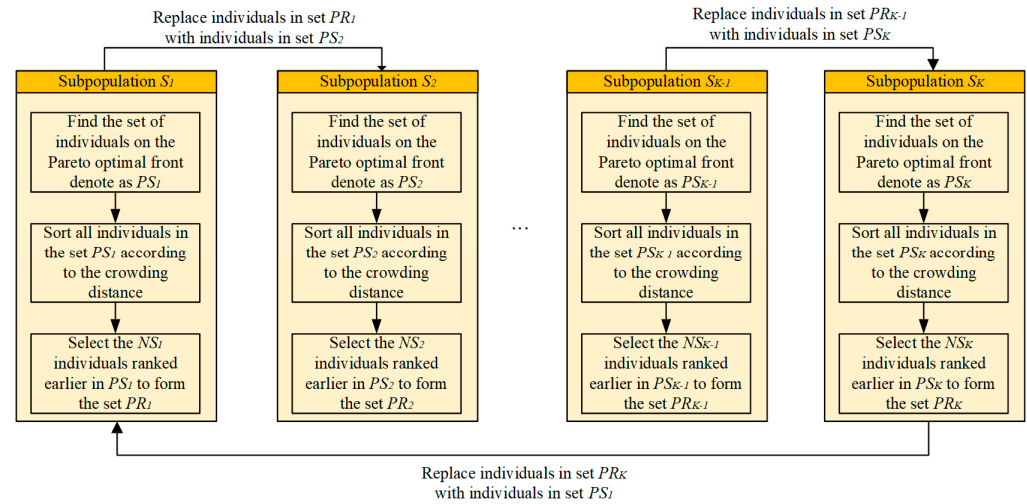


Figure 10. Multi-subpopulation migration operation.

3.6. Algorithm Complexity Analysis

The process of the IM2GWO algorithm consists of seven main steps: population initialization, individual fitness evaluation, fast non-dominated sorting, calculation of crowding distance, updating by genetic operators, sub-population migration, and merging of external archives. Assume that the number of subpopulations is N_S , the number of individuals in each sub-population is N_{pop} , the spatial dimension of each individual is D , and the size of the external archive is N_A .

The time complexity of population initialization is $O(N_S \cdot N_{pop} \cdot D)$. The time complexity of evaluating the fitness of individuals in each subpopulation is $O(N_S \cdot \log(N_{pop}))$. For the non-dominated sorting of each subpopulation, for N_{pop} individuals, the time complexity of fast non-dominated sorting is $O(N_S \cdot N_{pop}^2)$. The time complexity of calculating the crowding distance for each external archive is $O(N_S \cdot N_A \cdot \log(N_A))$.

In each iteration, genetic operators such as crossover and mutation are used to update individuals, and the time complexity is $O(N_S \cdot N_{pop} \cdot D)$, where $O(D)$ represents the complexity of genetic operations related to the dimension D . The total number of iterations of the algorithm is $MaxIt$, so the total time complexity of iterative updates is $O(MaxIt \cdot N_S \cdot N_{pop} \cdot D)$.

Every K iterations, elite individuals are selected and migrated. The number of migrated individuals is N_E , and the time complexity is $O(N_E \cdot N_S \cdot (MaxIt/K))$. After the iteration ends, every external archive is merged and globally non-dominated sorted, and the time complexity is $O(N_S^2 \cdot N_A^2)$.

In summary, the total time complexity is the sum of the time for initialization, all iterations, migration, and the final output. Considering that the time complexity of initializing the population and merging the external archives can be dominated by the iterative terms of the algorithm, and that the size of the external archive N_A is proportional to the number of population individuals N_{pop} , the total time complexity can be simplified to: $O(MaxIt \cdot N_S \cdot (\log(N_{pop}) + N_{pop}^2 + N_{pop} \cdot D))$.

4. Coverage Path Planning Based on Improved DP

After determining the ROIs to be covered and the access order for each UAV based on IM2GWO, multi-region coverage path planning can be carried out. As shown in Figure 11, the access order is $\{0 \rightarrow 3 \rightarrow 4 \rightarrow 2 \rightarrow 1 \rightarrow 5 \rightarrow 0\}$. The coverage path of the UAV consists of two parts: the inner coverage path and the outer transition path. It has been proven in research [26] that using antipodal point pairs as the entry and exit points of the target area can generate an approximately optimal solution for the coverage path.

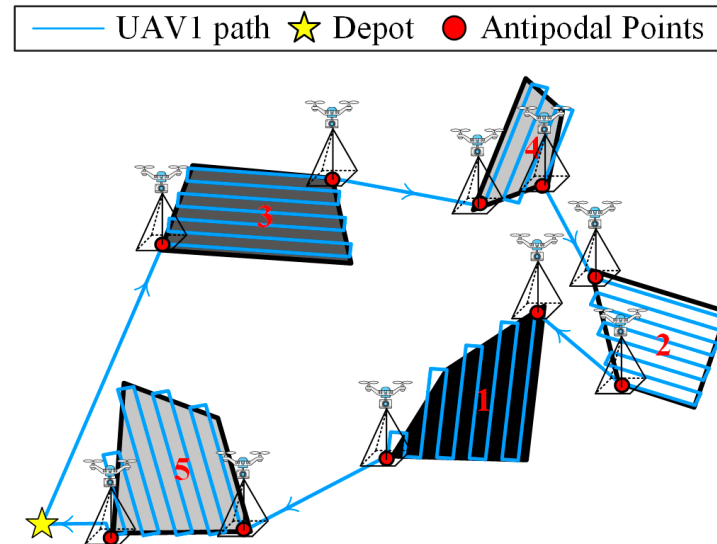


Figure 11. Schematic diagram of multi region coverage path.

For each ROI, define its antipodal pair set as $\{A_i\}_{i=1}^{N_s}$. Given a predetermined ROI visitation sequence, the optimal antipodal pair $\{(a_{i,1}, a_{i,2})\} \in A_i$ is selected for each ROI as the entry and exit points.

The path cost between consecutive ROIs is defined as the transition cost from the exit point $a_{i,2}$ of the i -th ROI to the entry point $a_{i+1,1}$ of the $i+1$ -th ROI:

$$t_{i,i+1}^{\min}(a_{i,2}, a_{i+1,1}) \triangleq \min_{a_{i+1,1} \in A_{i+1}} \left[t_{i,i+1}^{\text{inner}}(a_{i+1,1}, a_{i+1,2}) + t_{i,i+1}^{\text{outer}}(a_{i,2}, a_{i+1,1}) \right] \quad (24)$$

where $t_{i,i+1}^{\text{inner}}(a_{i+1,1}, a_{i+1,2})$ calculates the flight time from the entry point $a_{i+1,1}$ to the exit point $a_{i+1,2}$ of the $i+1$ -th ROI. $t_{i,i+1}^{\text{outer}}(a_{i,2}, a_{i+1,1})$ calculates the flight time from the exit point $a_{i,2}$ of the i -th ROI to the entry point $a_{i+1,1}$ of the $i+1$ -th ROI. Under this cost metric, the problem reduces to optimizing the exit point sequence $\{a_{i,2}\}_{i=1}^I$ to minimize the total flight time, formulated as:

$$\min_{\{a_{i,1}, a_{i,2}\} \in A_i} \sum_{i=0}^I t_{i,i+1}^{\min}(a_{i,2}, a_{i+1,1}) \quad (25)$$

This problem is solvable via DP using Bellman's equation sequence:

$$\text{Mintime}_{i+1}(a_{(i+1),2}) = \min_{\{a_{i,1}, a_{i,2}\} \in A_i} \left[\text{Mintime}_i(a_{i,2}) + t_{i,i+1}^{\min}(a_{i,2}, a_{i+1,1}) \right] \quad (26)$$

where $A_0 = A_{I+1} = \{\phi_{S_0}\}$ and $\text{Mintime}_0(\phi_{S_0}) = 0$. $\text{Mintime}_i(a_{i,2})$ represent the minimum time cost that can be achieved leading up to the point $a_{i,2}$ of ϕ_{S_i} .

Algorithm 1 provides the pseudocode for DP-based coverage path planning.

Algorithm 1: DP-based coverage path planning

Input: Set of ROI locations assigned to the k -th UAV Z_k ;
The access order Γ_k of ROIs assigned to the k -th UAV;
UAV flight speed v_k and rotation speed ω_k ;
FOV of UAV sensor $W \times L$.
Output: Set of entry and exit points of each ROI $\{(a_{i,1}, a_{i,2})\}_{i=1}^I$

- 1: Initialize set $Path_{I \times 2}$;
- 2: Rebel the ROIs of Z_k according to Γ_k ;
- 3: The set of antipodal pairs $\{A_i\}_{i=1}^I$ are computed by RCA [26].
- 4: Set $A_0 = A_{I+1} = \{\phi_{S_0}\}$, Compute $t_{i,i+1}^{\text{inner}}(a_{i+1,1}, a_{i+1,2})$ and $t_{i,i+1}^{\text{outer}}(a_{i,2}, a_{i+1,1})$ based on Equation (24);
- 5: Set $\text{Mintime}_0(\phi_{S_0}) \leftarrow 0$;
- 6: For $i = 0$ to I do
- 7: For each $\{(a_{i,1}, a_{i,2})\} \in A_i, i = 1, 2, \dots, I$ do
- 8: Compute $\text{Mintime}_{i+1}(a_{i+1,2})$ based on Equation (26)
- 9: Calculate $\tilde{a}_{i,2} = \arg\min_{\{(a_{i,1}, a_{i,2})\} \in A_i} [\text{Mintime}_i(a_{i+1,2}) + t_{i,i+1}^{\text{min}}(a_{i,2}, a_{i+1,2})]$;
- 10: Calculate $\tilde{a}_{i+1,1} = \arg\min_{\{(a_{i+1,1}, a_{i+1,2})\} \in A_{i+1}} [t_{i,i+1}^{\text{inner}}(a_{i+1,1}, a_{i+1,2}) + t_{i,i+1}^{\text{outer}}(a_{i,2}, a_{i+1,1})]$;
- 11: Set $\text{Pre-path}_{i+1}(a_{i+1,2}) \leftarrow (\tilde{a}_{i,2}, \tilde{a}_{i+1,2})$;
- 12: End For
- 13: End For
- 14: Set $Path \leftarrow \emptyset$;
- 15: For $i = 0$ to I do
- 16: Set $Path_{I \times 2} \leftarrow \text{Pre-path}_{I+1-i}(a_{I+1-i,2}) \cup Path$;
- 17: End For
- 18: Return $\{(a_{i,1}, a_{i,2})\}_{i=1}^I \leftarrow Path_{I \times 2}$

5. Simulation Results

5.1. Simulation Parameter Setting

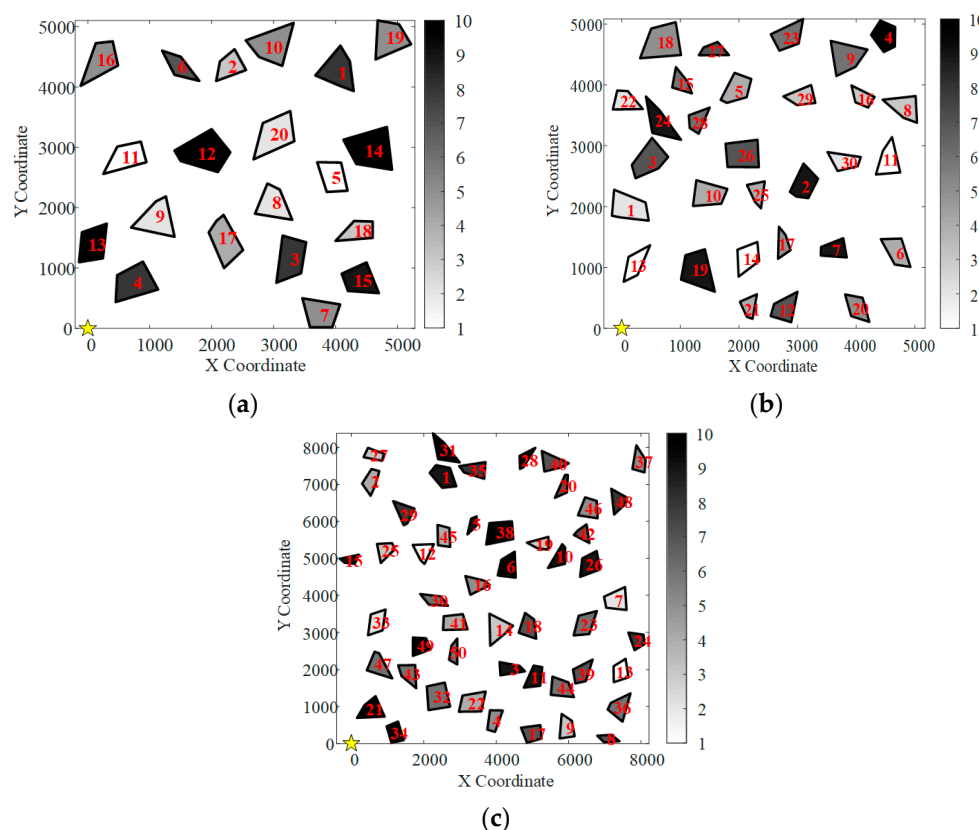
Three task scenarios of varying complexity are simulated to demonstrate the efficacy of the proposed method, where the numbers of UAVs and ROIs gradually increase. The initial position distribution and priorities of the ROIs are shown in Figure 12, where different priorities are represented by a colormap. The darker the colormap, the higher the priority, and the corresponding initial coverage benefits are set as integers between $[0, 10]$. For the convenience of subsequent task planning, each ROI is numbered in advance and highlighted in red font. The yellow star symbol indicates the starting/ending position of the multiple UAVs. Table 2 shows the specific scenario parameters. Table 3 shows the performance indicators of multiple UAVs.

Table 2. Parameters of coverage task scenario.

Scenario	Number of UAV	Number of ROI	Size of Mission Area
1	3	20	5000 m $\times$ 5000 m
2	5	30	5000 m $\times$ 5000 m
3	7	50	8000 m $\times$ 8000 m

Table 3. The performance indicators of multiple UAVs.

Attribute	Value
Flight speed	20 m/s
Flight altitude	200 m
Yaw angular velocity	0.25 rad/s
Maximum endurance	3000 s
FOV size	50 m × 100 m

**Figure 12.** Schematic diagram of coverage task scenario (a) 20 ROIs; (b) 30 ROIs; (c) 50 ROIs.

5.2. Comparison of Multi-Objective Optimization Performance

Three benchmark algorithms were selected for the comparative analysis. Non-dominated Sorting Genetic Algorithm II (NSGA-II) [29] and Strength Pareto Evolutionary Algorithm 2 (SPEA2) [30] are two classic multi-objective evolutionary algorithms (MOEA). Their core elements are population evolution mechanisms such as survival of the fittest and gene mutation. Although they cannot guarantee the achievement of global optimality, they are excellent in terms of their search ability, simplicity, and efficiency. The bi-subpopulation coevolutionary immune algorithm (BCIA) [31] is a newly proposed immune algorithm. This algorithm improves the lower limit of population diversity through the bi-subpopulation coevolution mechanism and shows good performance in the multi-UAV task allocation problem. NSGA-II and SPEA 2 implementations utilize the PlatEMO v4.13 in MATLAB 2021a [32], employing order crossover and weak mutation for discrete multi-objective optimization. For BCIA, the dominant population size is set to 100 and the elite population size is set to 20, with an external archive capacity of 100. All algorithms share an identical initial population size ($N_{pop} = 200$) and maximum iterations ($MaxIt = 300$) to ensure comparability.

The Pareto optimal fronts generated under different scenarios are shown in Figure 13. Comparative analysis shows that the Pareto front distributions of each algorithm exhibit significant differential characteristics under scenarios of different complexities. In Scenario 1, the Pareto fronts generated by each algorithm do not show significant hierarchical characteristics, and their convergence performances are approximately similar. The performance differences of algorithms will show measurable changes as the complexity of the problem increases. As the scale of the problem grows, the stratification phenomenon of the Pareto front further expands. The IM2GWO demonstrates remarkable superiority; the Pareto solution set it obtains forms a complete outer envelope structure in the objective space and has an obvious dominant position. The solution set distributions of the classic multi-objective algorithms SPEA2 and NSGA-II show a local convergence tendency, forming higher density aggregation characteristics in specific regions of the objective space. Notably, IM2GWO maintains solution set convergence while achieving superior Pareto front distribution uniformity across the objective space.

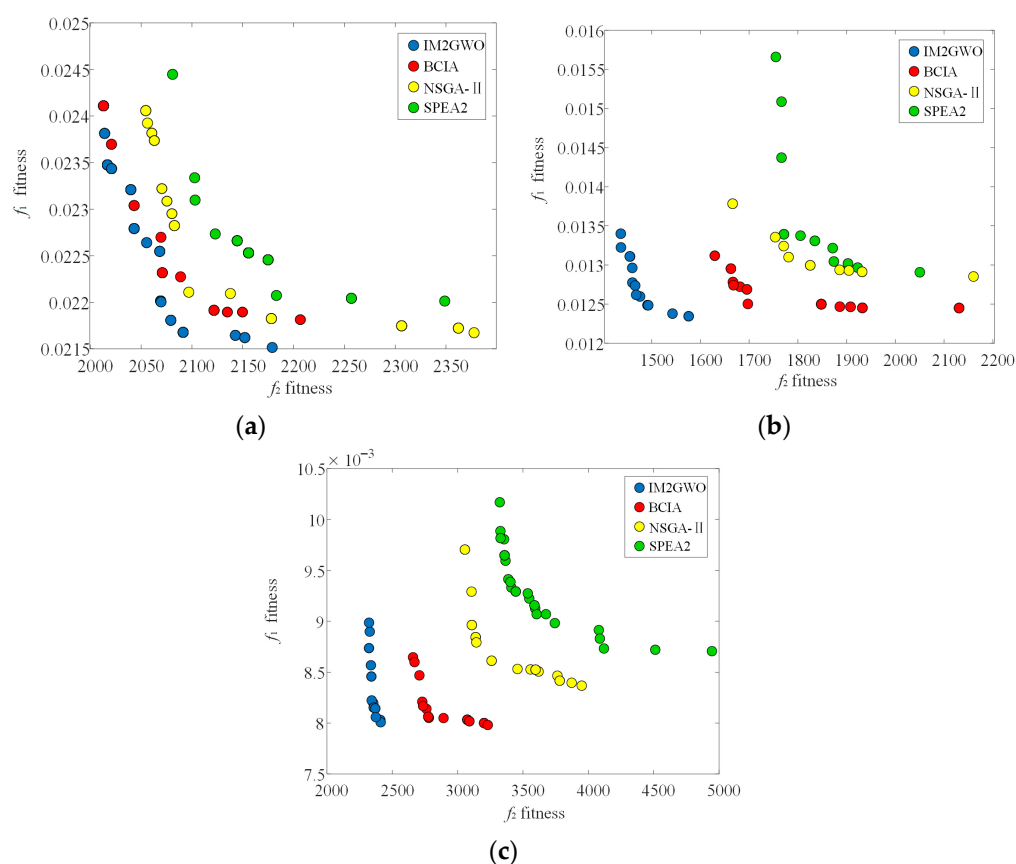


Figure 13. Comparison of algorithm Pareto fronts in different scenarios. (a) The pareto optimal fronts in Scenario 1; (b) The pareto optimal fronts in Scenario 2; (c) The pareto optimal fronts in Scenario 3.

The convergence curves of multi-objective functions are shown in Figure 14. After 300 iterations, IM2GWO maintains a stable convergence trend in the bi-objective space, and the final convergence value is improved by 12.7–23.4% compared with the benchmark algorithm. Moreover, it achieves the optimal performance. This advantage is attributed to the adaptive genetic operator and the dominant individual migration strategy. In a small-scale scenario, the fitness values of the BCIA algorithm are approximately the same as those of IM2GWO, indicating its potential applicability in small-scale scenarios. However, when the problem dimension is extended to medium and large scales, the performance differences between the algorithms increase. IM2GWO achieves faster convergence and superior solution quality, outperforming benchmarks across all test scenarios.

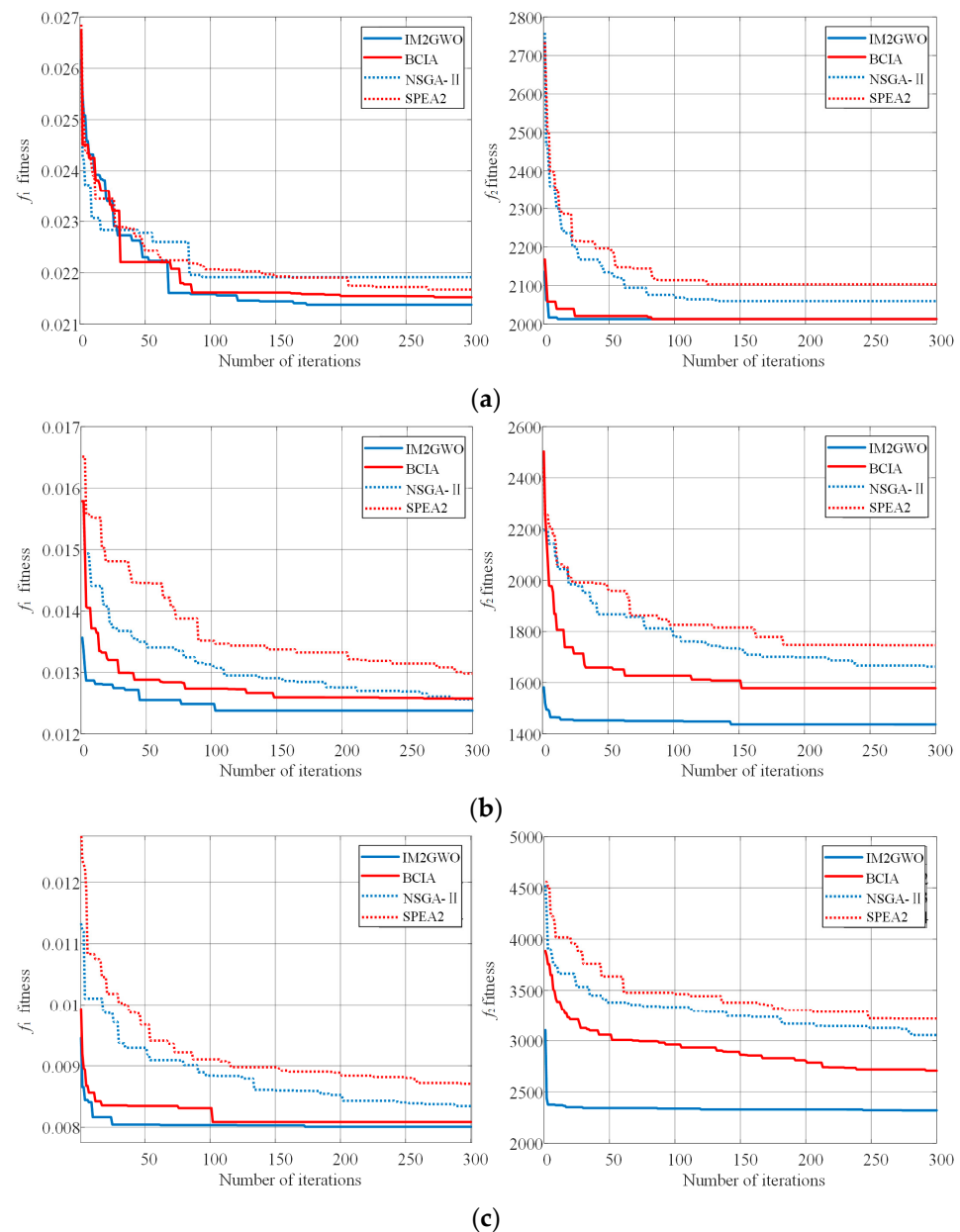


Figure 14. Convergence curves of algorithm fitness values under different scenarios (a) Comparison of algorithm convergence curves in Scenario 1; (b) Comparison of algorithm convergence curves in Scenario 2; (c) Comparison of algorithm convergence curves in Scenario 3.

5.3. Comparison of Algorithm Execution Time

We conducted 50 independent trials in three different scenarios to compare the runtime of algorithms and the efficiency of solutions. Figure 15 shows the execution time per iteration of the comparative algorithm across various scenarios. Since the BCIA algorithm needs to perform non-dominated sorting multiple times to select elite individuals, it takes the longest time. The average iteration time of SPEA2 is the shortest because it prematurely falls into local convergence, resulting in poor performance. In the three scenarios, the average running times of IM2GWO are 0.204 s, 0.312 s, and 0.522 s, respectively, being 50.2%, 55.5%, and 59.3% shorter than those of the BCIA algorithm. It can be seen that as the problem scale increases, the advantages of the IM2GWO algorithm in terms of both solution quality and solution efficiency are enhanced.

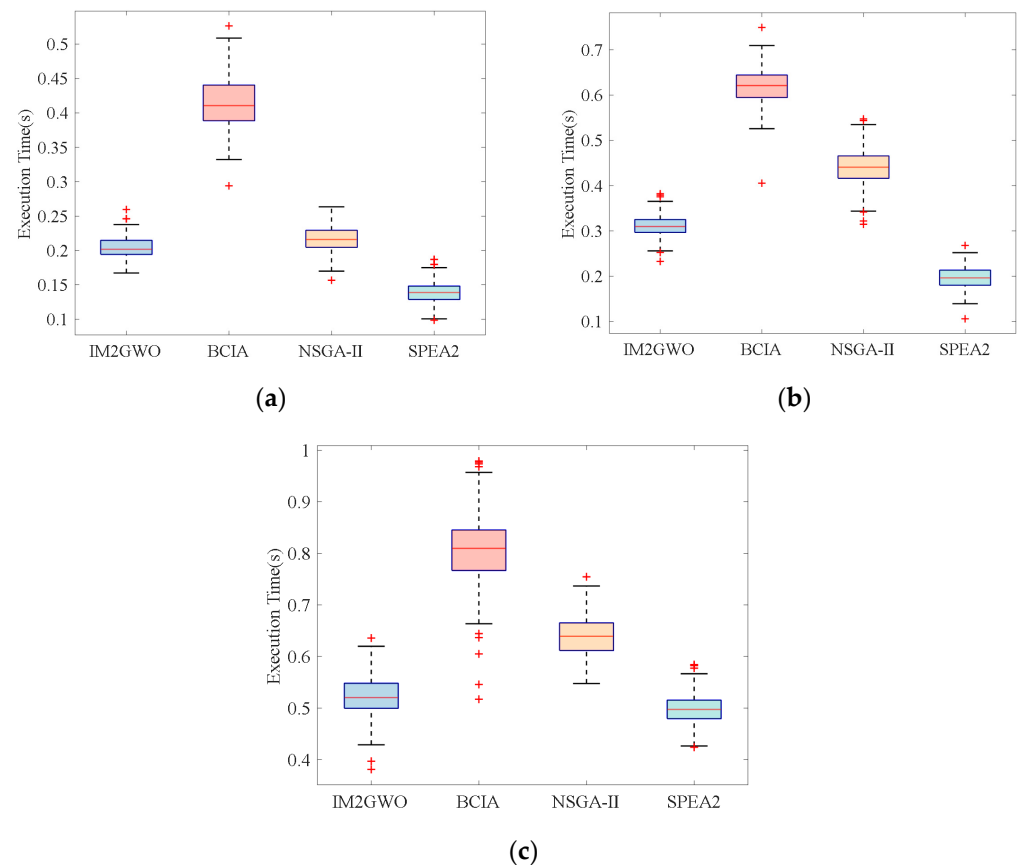


Figure 15. The execution time per iteration of the comparative algorithm across various scenarios (a) Scenario 1; (b) Scenario 2; (c) Scenario 3.

5.4. Complete Method Validation

The alternative ROI allocation schemes were obtained through the Pareto optimal solution set of multi-objective optimization. The allocation scheme with the shortest task completion time was selected for coverage path planning to verify the performance of the complete method. The multi-UAV multi-area coverage path finally generated is shown in Figure 16. It can be seen that the coverage path generated by the method in this paper can evenly distribute the workload of multiple UAVs and preferentially cover high-priority ROIs.

Based on the motion parameters of the UAV and the coverage path, the actual coverage effectiveness indicators can be calculated, including the maximum task completion time (MTCT), the average task completion time (ATCT), the total coverage benefit (TCB), and the average coverage benefit (ACB). Notably, since the multi-objective fitness values derive from range estimation modelling, the actual task completion time post-DP optimization falls below predicted values. This performance gap arises because the voyage estimation model inherently overestimates task duration—a conservative approach ensuring feasibility. DP’s actual time reduction validates its optimization capability.

Table 4 shows the statistical analysis results of coverage effectiveness indicators in different scenarios. In Scenario 1, both IM2GWO and BCIA achieve identical task completion times (1634.84 s). Compared with the baseline method, our method effectively reduces the average UAV completion time (1611.02 s), confirming enhanced workload balancing. Simultaneously, it retains a competitive coverage benefit (40.83), merely 5.1% below the peak performance—demonstrating effective multi-objective trade-off.

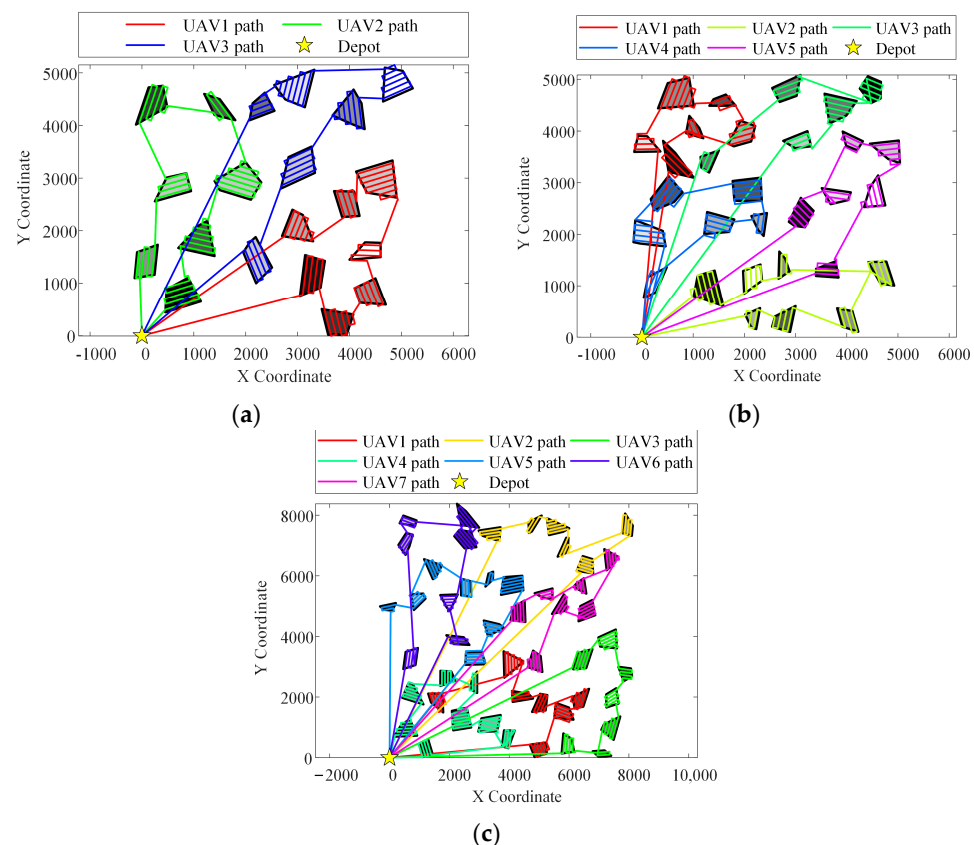


Figure 16. Results of multi UAV multi-region coverage paths in different scenarios. (a) Scenario 1; (b) Scenario 2; (c) Scenario 3.

Table 4. Statistical analysis results of coverage effectiveness indicators in different scenarios.

Scenario	Method	MTCT (s)	ATCT (s)	TCB	ACB
1	IM2GWO	1634.84	1611.02	40.83	13.61
	BCIA	1634.84	1626.40	40.48	13.49
	NSGA-II	1711.24	1683.89	40.07	13.36
	SPEA2	1818.21	1815.83	43.04	14.35
2	IM2GWO	1223.65	1192.66	76.30	15.26
	BCIA	1272.75	1201.32	74.61	14.92
	NSGA-II	1333.08	1290.33	72.85	14.57
	SPEA2	1313.39	1272.15	78.09	15.62
3	IM2GWO	1870.49	1611.02	111.18	15.88
	BCIA	1903.13	1626.40	112.13	16.02
	NSGA-II	2782.31	1683.89	104.32	14.90
	SPEA2	2979.40	1815.83	98.51	14.07

In Scenario 2, the proposed method demonstrates significant timeliness advantages: both the UAV maximum task completion time (1223.65 s) and the UAV average task completion time (1192.44 s) are optimal. This validates algorithmic robustness across diverse scenarios. Notably, while maintaining temporal efficiency, the coverage gain of the IM2GWO algorithm reaches 76.30, trailing SPEA2 only by a slight margin (1.4%). Although SPEA2 maximizes coverage gain, it exhibits critical load balancing limitations that hinder effective multi-objective optimization equilibrium.

In Scenario 3, the proposed method exhibits enhanced timeliness advantages. It achieves optimal maximum (1883.13 s) and average (1829.75 s) task completion times—verifying scalability for large-scale problems. While total and average coverage ben-

efits trail BCIA by marginal margins, NSGA-II and SPEA2 display significant performance degradation at scale, demonstrating limited applicability to large-scale instances.

6. Conclusions

In this study, we addressed the challenge of multi-UAV collaborative coverage mission planning in maritime search and rescue scenarios by developing a hierarchical decoupling optimization framework. This framework decomposes the complex problem into two stages: task allocation and path planning. Specifically, we first constructed a voyage estimation model based on regional geometric features and the BFP coverage mode, establishing a region-coverage time association matrix. Subsequently, we proposed a multi-objective algorithm, IM2GWO, which integrates adaptive genetic operators and a multi-population coevolutionary mechanism. Finally, we constructed optional coverage modes and transformed path planning into a multi-stage decision-making problem, employing an improved dynamic programming (DP) approach to generate globally optimal coverage paths. Experimental results demonstrate that IM2GWO outperforms comparison algorithms in Pareto front distribution across three different scale scenarios, with advantages magnifying as the problem size increases. The DP-based path planning module exhibits significant timeliness and economic benefits by reducing coverage costs. Beyond these findings, our work contributes to the field by providing a scalable solution for UAV-based coverage optimization, with potential applications in disaster response and environmental monitoring. Although the core method proposed in this study has been rigorously verified through simulations and tests under controlled conditions representing maritime intervention operations, the complete integrated system still awaits formal field trials in actual maritime operations. These trials are planned to be carried out in future work.

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

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