RESEARCH ARTICLE

Optimal Allocation of Heterogeneous UAV Swarms for Reservoir Inspection with Task Decomposition

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Abstract

To meet the efficiency and economy requirements of unmanned aerial vehicle (UAV) inspection for large watershed, long-distance and multi-measurement-point reservoirs, this paper focuses on the optimal allocation problem of heterogeneous UAV swarms for reservoir inspection with task decomposition. Firstly, the four decomposable dimensions of reservoir inspection tasks (spatial decomposition, time decomposition, measurement point decomposition, and data accuracy decomposition) are clarified, and the performance metrics and constraints of heterogeneous UAV swarms are defined. Secondly, inspection success models and inspection cost models are constructed to form a dual-objective optimization model. Then, an efficient solution based on the greedy algorithm is designed to realize the optimal allocation of UAV swarms. Finally, the effectiveness and practicality of the models and solution are verified through a case study. The results show that the proposed models and solution can effectively improve the success of reservoir inspection and reduce the total inspection cost.

Keywords: reservoir UAV inspection, task decomposition, heterogeneous UAV swarm, optimal allocation, dual-objective optimization.

1 Introduction

As the core infrastructure for water resource regulation, flood control and disaster reduction, and irrigation water supply, reservoirs, especially large-basin and long-distance reservoirs, their safe operation is directly related to people's lives and property safety and regional economic and social development. Traditional reservoir inspection relies on manual foot patrols, vehicle inspections and other methods, which have disadvantages such as low inspection efficiency, many blind areas, high risk coefficient, and high cost, which can no longer meet the needs of refined and regular inspection of modern reservoirs [1].

UAV inspection has been widely used in the field of reservoir inspection due to its advantages of strong flexibility, wide coverage, high inspection efficiency,

Submitted: 26 February 2026
Accepted: 31 March 2026
Published: 08 April 2026

Vol. 2, **No.** 2, 2026.
10.62762/TSSR.2026.977710

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Citation
Mo, Y., Gui, F., Chynybaev, M., Chymyrov, A., Wu, W., & Zhu, J. (2026). Optimal Allocation of Heterogeneous UAV Swarms for Reservoir Inspection with Task Decomposition. *ICCK Transactions on Systems Safety and Reliability*, 2(2), 101–111.

and relatively low cost. With the development of UAV technology, heterogeneous swarms have gradually replaced the single UAV inspection mode, which can flexibly adapt to different scenarios according to inspection task requirements and further improve inspection efficiency and quality [2].

At present, certain progress has been made in the research related to UAV inspection task allocation and task decomposition, mainly focusing on three aspects: single-objective optimization, task decomposition methods, and heterogeneous swarm allocation [3].

In terms of UAV inspection task allocation, scholars mostly focus on single-objective optimization: one type of research takes the maximization of inspection reliability/task utility as the objective, improves the task completion rate and robustness by matching UAV capabilities with task requirements, for example, constructing the matching relationship between UAV performance and task difficulty and optimizing the allocation strategy in scenarios such as power inspection [4, 5]; the other type of research takes the minimization of inspection cost as the objective, reduces the number of UAV sorties, shortens flight time and resource consumption through the integration of path and scheduling optimization under time window constraints, thereby reducing the inspection cost [6]. However, such research is still dominated by a single objective, lacking a systematic modeling and unified solution framework for the collaborative trade-off of dual objectives (or multi-objectives) such as "reliability-economy", which leads to difficulties in balancing inspection quality and cost constraints in engineering applications [7].

In terms of task decomposition, existing research mainly focuses on spatial decomposition and time period decomposition, for example, dividing a large inspection area into multiple sub-areas based on regional division (such as Voronoi diagram), and then conducting coverage path planning and task allocation respectively [8]; or adopting an iterative joint optimization framework of "task decomposition-allocation-path planning" to decompose complex coverage tasks into executable subtasks and gradually converge to a feasible solution [9]. At the same time, some studies carry out dynamic reallocation according to point benefit/uncertainty for multi-point continuous monitoring tasks, but their splitting granularity is more around monitoring benefits and environmental changes, and few introduce engineering measurement constraints such as accuracy grading [10]. Aiming at the particularity of reservoir/dam inspection (dense distribution of measurement points, significant differences in data accuracy and surveying and mapping constraints), the existing published research is mostly concentrated on the task/route design and accuracy control required for photogrammetry and 3D modeling, and a systematic rule and allocation mechanism for "measurement point splitting-accuracy splitting" has not yet been formed [11].

In terms of heterogeneous swarm allocation, research usually emphasizes the performance differences between UAVs (such as speed, endurance, load, communication and task constraints), and establishes an allocation model or distributed coordination mechanism under heterogeneous resource constraints accordingly [12]; however, many methods still regard tasks as indecomposable or weakly decomposable objects, resulting in insufficient adaptability in complex engineering inspection scenarios of large watershed, long-distance and multi-measurement-point inspection of reservoirs [13].

Reservoir inspection tasks have significant decomposable characteristics, which can be decomposed from four dimensions: space, time, measurement point, and data accuracy. These decomposable characteristics provide the possibility for the optimal allocation of heterogeneous swarms-through reasonable task decomposition, different types of subtasks are assigned to the most suitable UAVs, which can not only ensure the successful completion of inspection tasks but also control inspection costs. However, current research on UAV inspection task allocation for reservoirs mostly ignores the task decomposable characteristics or only focuses on a single objective (such as maximizing success probability or minimizing cost), which is difficult to achieve the dual needs of reliable inspection and economic efficiency.

This paper focuses on the optimal allocation problem under task decomposition in the scenario of heterogeneous UAV swarm reservoir inspection. The innovations of this paper are mainly reflected in three aspects: 1) It improves the decomposition of reservoir inspection tasks, clarifies four core decomposable dimensions of space, time, measurement point and data accuracy, and proposes systematic decomposition rules adapted to the reservoir inspection scenario; 2) It constructs a dual-objective optimization model for success and cost, which takes into account both inspection reliability and economy and adapts to the inspection optimization demand of large watershed reservoirs; 3) It designs a simple and efficient algorithm to solve the dual-objective optimization model, obtain the optimal task scheduling scheme.

2 Problem Description

2.1 Task Decomposition

According to the engineering practice of UAV inspection for large watershed, long-distance and multi-measurement-point reservoirs, this section clarifies the four decomposable dimensions of reservoir inspection tasks.

Spatial decomposition

The entire reservoir inspection area is divided into multiple non-overlapping and continuous subspaces according to geographic coordinates, watershed zoning and other methods. The area of each subspace is matched with the endurance and load capacity of UAVs to avoid inspection failure caused by overlong flight distance and excessive load of UAVs; the boundaries of subspaces are clear to avoid inspection blind areas and repeated inspections. For example, a large reservoir is divided into three sub-areas: upper reaches, middle reaches and lower reaches according to the watershed, and each sub-area is further divided into several small subspaces to adapt to UAVs with different endurance capacities.

Time decomposition

The entire inspection cycle is divided into multiple non-overlapping sub-periods. Sub-periods are reasonably divided in combination with meteorological conditions (wind speed, precipitation, visibility), UAV flight restrictions (such as night flight taboos) and inspection urgency; the duration of each sub-period is matched with the endurance time of UAVs and the complexity of subtasks to ensure that UAVs can complete the corresponding subtasks within the sub-periods. For example, the one-day inspection task is divided into two sub-periods: morning (8:00-12:00) and afternoon (14:00-18:00), avoiding the high temperature at noon and the low visibility at night.

Measurement point decomposition

All measurement points of reservoir inspection are divided into multiple sub-sets of measurement points according to type, distribution density and importance. The number of measurement points in each sub-set is matched with the load of UAVs and the requirements of inspection accuracy; important measurement points are split separately or classified into the same sub-set, and high-performance UAVs are assigned first to ensure the inspection success probability. For example, the measurement points of the reservoir dam are divided into two sub-sets: crack measurement points and settlement measurement points, and the water level and water quality measurement points are divided into another sub-set, which are assigned to different types of UAVs respectively.

Data accuracy decomposition

According to the different needs of reservoir inspection, the requirements of inspection data accuracy are divided into multiple levels. High-precision requirements correspond to important subtasks (such as dam crack detection), and medium and low-precision requirements correspond to conventional subtasks (such as inspection of surface garbage in the reservoir area); the data accuracy level is matched with the sensor accuracy and flight height of UAVs to avoid cost waste caused by high-performance UAVs completing low-precision tasks or inspection failure caused by low-performance UAVs completing high-precision tasks.

2.2 Heterogeneous UAV Swarms

The heterogeneous UAV swarm in this paper refers to an inspection swarm composed of multiple types of UAVs with different models, performances and costs. Each UAV has differences in flight speed, endurance time, load capacity, sensor accuracy, flight cost and inspection success probability, and can adapt to different types of inspection subtasks. For example, the swarm includes three types of UAVs: Type 1 (high-performance): long endurance time, high sensor accuracy, high inspection success probability, but high flight cost; Type 2 (conventional): moderate performance in all aspects and moderate cost; Type 3 (economic): short endurance time, low sensor accuracy, low inspection success probability, but low flight cost.

This paper selects six types of parameters of heterogeneous UAV swarms to construct the optimization model, as follows:

1. Endurance time t_i: the maximum continuous flight time of the i-th type of UAV in a single flight (unit: h);
2. Flight speed v_i: the average flight speed of the i-th type of UAV (unit: km/h);
3. Sensor accuracy p_i: the detection accuracy of the

sensor of the i-th type of UAV (unit: %), with a value range of $[0, 1]$. The higher the accuracy, the more accurate the inspection data and the higher the inspection success probability;

4. Inspection success probability $s_{i,j}$: the single inspection success probability of the i-th type of UAV completing the j-th type of subtask (unit: %), with a value range of $[0, 1]$, which is determined by the matching degree between UAV performance and subtask requirements;

5. Unit flight cost c_i: the cost of the i-th type of UAV per flight hour (unit: CNY/h), including energy consumption cost, maintenance cost, etc.;

6. Quantity constraint n_i: the available quantity of the i-th type of UAV (unit: units), i.e., the maximum callable quantity of the i-th type of UAV in the heterogeneous swarm.

According to the practice of reservoir inspection and the characteristics of heterogeneous swarms, this paper defines four types of constraints for the construction of the optimization model.

1. Time constraint: the flight time of the UAV to complete a certain subtask shall not exceed its endurance time;

2. Quantity constraint: the number of UAVs assigned to each subtask shall not exceed the available quantity of the corresponding type of UAVs;

3. Matching constraint: the UAV performance shall meet the data accuracy requirements of the corresponding subtask, otherwise the UAV cannot be assigned to the subtask;

4. Completeness constraint: all split subtasks shall be assigned at least one UAV to complete, with no missing subtasks.

2.3 Dual-objective Optimization

The optimization objectives of this paper are maximizing the total success probability and minimizing the total cost, which belong to a dual-objective optimization problem. The linear weighted sum method is adopted to transform the dual-objective optimization problem into a single-objective optimization problem, and the importance of the two objectives is balanced by setting weight coefficients. The weight coefficients can be adjusted according to the actual needs of reservoir inspection (e.g., the key inspection scenario focuses on the success probability, and the conventional inspection scenario focuses on the cost), which enhances the flexibility of the model.

3 Optimization Model Construction

3.1 Symbol Definition

To facilitate the model construction, the following symbols are defined in this paper:

3.1.1 Task-related symbols

- J: the total number of split subtasks, $j = 1, 2, \ldots, J$;
- w_j: the workload of the j-th subtask (unit: km, or number of measurement points);
- q_j: the data accuracy requirement of the j-th subtask (unit: %), with a value range of $[0, 1]$;
- u_j: the importance weight of the j-th subtask, with a value range of $[0, 1]$. The higher the importance, the greater the weight.

3.1.2 UAV-related symbols

- I: the number of types of heterogeneous UAV swarms, $i = 1, 2, \ldots, I$;
- t_i: the endurance time of the i-th type of UAV (unit: h);
- v_i: the flight speed of the i-th type of UAV (unit: km/h);
- p_i: the sensor accuracy of the i-th type of UAV (unit: %), with a value range of $[0, 1]$;
- $s_{i,j}$: the single inspection success probability of the i-th type of UAV completing the j-th subtask (unit: %), with a value range of $[0, 1]$;
- c_i: the unit flight cost of the i-th type of UAV (unit: CNY/h);
- n_i: the available quantity of the i-th type of UAV (unit: units).

3.1.3 Decision variables

- $x_{i,j}$: 0–1 variable, $x_{i,j} = 1$ means the i-th type of UAV is assigned to the j-th subtask, and $x_{i,j} = 0$ means not assigned;
- $k_{i,j}$: the number of sorties of the i-th type of UAV assigned to the j-th subtask (unit: sorties), taking a non-negative integer value;
- $t_{i,j}$: the single flight time of the i-th type of UAV to complete the j-th subtask (unit: h).

3.1.4 Weights and constants

- α: the weight coefficient of the total success probability, with a value range of $[0, 1]$;
- β: the weight coefficient of the total cost, with a value range of $[0, 1]$, and $\alpha + \beta = 1$;
- λ: the cost normalization coefficient, used to convert the total cost and total success probability into the same order of magnitude for convenient weighted calculation.

3.2 Objective Function Construction

This paper constructs a dual-objective optimization function for maximizing the total success probability and minimizing the total cost, and adopts the linear weighted sum method to transform it into a single-objective optimization function to simplify the solution process.

Firstly, the single flight time $t_{i,j}$ of the i-th type of UAV to complete the j-th subtask is calculated, which is determined by the workload of the subtask and the flight speed of the UAV:

$$t_{i,j} = \frac{w_j}{v_i}$$

The constraint condition is $t_{i,j} \leq t_i$, i.e., the flight time shall not exceed the endurance time; if this constraint is not satisfied, then $x_{i,j} = 0$, i.e., the UAV cannot be assigned to the subtask.

3.2.1 Objective 1: Maximizing the total success probability

The entire success probability is the weighted sum of the inspection success probabilities of all subtasks, and the weight reflects the importance of the subtasks. The inspection success probability of the j-th subtask is determined by the type and number of sorties of UAVs assigned to the subtask—the more the sorties, the higher the success probability.

The calculation of the inspection success probability S_j of the j-th subtask is:

$$S_j = 1 - \prod_{i=1}^{I} (1 - s_{ij})^{k_{ij}}$$

where $(1 - s_{ij})$ is the failure probability of the i-th type of UAV completing the j-th subtask in a single flight, $(1 - s_{ij})^{k_{ij}}$ is the probability that all k sorties of the i-th type of UAV fail, and $1 - \prod_{i=1}^{I}(1 - s_{ij})^{k_{ij}}$ is the probability that at least one sortie of UAV successfully completes the j-th subtask, i.e., the inspection success probability of the subtask.

The calculation of the total success probability S_{total} is:

$$S_{\text{total}} = \sum_{j=1}^{J} u_j \cdot S_j = \sum_{j=1}^{J} u_j \left[1 - \prod_{i=1}^{I} (1 - s_{ij})^{k_{ij}} \right]$$

Thus we get the optimization objective as max S_{total}.

3.2.2 Objective 2: Minimizing the total cost

The total cost of reservoir UAV inspection is determined by the flight time, number of sorties and unit flight cost of each UAV.

The calculation of the total cost C_{total} is:

$$C_{\text{total}} = \sum_{i=1}^{I} \sum_{j=1}^{J} k_{ij} \cdot t_{ij} \cdot c_i$$

where $k_{ij} \cdot t_{ij}$ is the total flight time of the i-th type of UAV assigned to the j-th subtask, and c_i is the unit flight cost.

Thus we get the optimization objective as $\min C_{\text{total}}$.

Since the total success probability S_{total} (value range $[0, 1]$) and the total cost C_{total} (positive value) have a large order of magnitude difference, the total cost needs to be normalized first, and then the linear weighted sum method is adopted to transform it into a single-objective optimization function.

The calculation formula of total cost normalization is:

$$C'_{\text{total}} = 1 - \frac{C_{\text{total}} - C_{\text{min}}}{C_{\text{max}} - C_{\text{min}}}$$

where C_{min} is the minimum total cost, corresponding to the cost of assigning all subtasks to economic UAVs; C_{max} is the maximum total cost, corresponding to the cost of assigning all subtasks to high-performance UAVs. After normalization, $C'_{\text{total}} \in [0, 1]$, which is of the same order of magnitude as the total success probability.

Thus we get the single-objective optimization function as:

$$\max F = \alpha \cdot S_{\text{total}} + \beta \cdot C'_{\text{total}}$$

where $\alpha + \beta = 1$. The larger the α, the more emphasis on the total success probability; the larger the β, the more emphasis on the total cost.

3.3 Constraint Conditions

According to the constraints defined in section 2.2, the constraint inequalities are obtained:

1. Time constraint (flight time shall not exceed endurance time):

$$t_{i,j} \leq t_i, \quad \forall i, j$$

2. Quantity constraint (the number of assigned sorties shall not exceed the available quantity):

$$\sum_{j=1}^{J} k_{ij} \cdot x_{i,j} \leq n_i, \quad \forall i$$

3. Matching constraint (sensor accuracy meets data accuracy requirements):

$$p_i \geq q_j, \quad \forall i, j$$

otherwise $x_{i,j} = 0$;

4. Completeness constraint (all subtasks are assigned UAVs):

$$\sum_{i=1}^{I} x_{i,j} \geq 1, \quad \forall j$$

5. Decision variable constraint (N is a non-negative integer):

$$x_{i,j} \in \{0, 1\}, \quad k_{i,j} \in N, \quad \forall i, j$$

4 Fast greedy optimal algorithm

4.1 Basic Idea

With the optimization model constructed above, a simple and efficient algorithm is designed based on the greedy algorithm, taking into account both solution accuracy and efficiency.

1. **Task priority sorting.** All subtasks are sorted by priority according to the importance weight u_j and data accuracy requirement q_j of the subtasks. The higher the priority of the subtask, the earlier it is assigned.

2. **UAV matching.** For each subtask with a certain priority, the types of UAVs that meet the matching constraint ($p_i \geq q_j$) and time constraint ($t_{i,j} \leq t_i$) are screened out, the cost performance ratio (i.e., success probability/cost) of each type of UAV is calculated, and the UAV type with the highest cost performance ratio is selected to be assigned to the subtask.

3. **Sortie optimization.** For the subtasks with assigned UAV types, the minimum number of sorties $k_{i,j,\min}$ that meets the minimum inspection success probability requirement of the subtask and the maximum number of sorties $k_{i,j,\max}$ that does not exceed the available quantity of UAVs are calculated. Within this range, the number of sorties $k_{i,j}$ is traversed to maximize the local comprehensive objective function F corresponding to the subtask, so as to obtain the optimal number of sorties for the subtask.

4. **Iterative adjustment.** After the assignment of all subtasks is completed, check whether all constraint conditions are satisfied. If there are constraint violations (such as insufficient number of UAVs), adjust the UAV assignment and number of sorties of low-priority subtasks until all constraints are satisfied, and the optimal allocation scheme is obtained.

4.2 Algorithm Design

The proposed fast greedy optimal algorithm has following 8 steps.

Step 1: Initialize parameters.

Input all subtask parameters (J, w_j, q_j, u_j), UAV parameters $(I, t_i, v_i, p_i, s_{ij}, c_i, n_i)$, weight coefficients (α, β), normalization coefficient (λ), and initialize decision variables $x_{ij} = 0, k_{ij} = 0$.

Step 2: Sort subtasks by priority.

Calculate the priority score $P_j = h_j u_j + (1 - h_j) q_j$ of each subtask (the weight h_j can be adjusted), sort the subtasks in descending order of P_j to obtain the sorted subtask sequence $j_1, j_2, \ldots, j_J$, where j_1 has the highest priority.

Step 3: Initialize the available quantity of UAVs.

Let the remaining available quantity of the i-th type of UAV be $n_i = n_i$.

Step 4: Iterative assignment of subtasks.

For each sorted subtask $j_m (m = 1, 2, \ldots, J)$:

(4.1) **Screen feasible UAV types:** screen the set of UAV types I_{jm} that satisfy $p_i \geq q_{jm}$ and

$$t_{ijm} = \frac{w_{jm}}{v_i} \leq t_i$$

(4.2) **Calculate cost performance ratio:** for $\forall i \in I_{jm}$, calculate the cost performance ratio:

$$r_{ijm} = s_{ijm}/(t_{ijm} \cdot c_i)$$

(4.3) **Select the optimal UAV type:** select the UAV type i^* with the maximum r_{ijm}, and set

$$x_{i^*} = 1$$

(4.4) **Optimize the number of sorties:** set the minimum success probability $S_{jm,\min}$ of the subtask (e.g., 90%), calculate the minimum number of sorties $k_{\min} = \ln(1 - S_{jm,\min})/\ln(1 - s_{i^*,jm})$; calculate the maximum workload per sortie/maximum flight distance per sortie of UAV $v_i \cdot t_i$, calculate the minimum number of sorties required for a single task $\lceil W_{jm}/(v_i \cdot t_i)\rceil$, calculate the maximum number of sorties $k_{\max} = \min(n_i^*, \lceil W_{jm}/(v_i \cdot t_i)\rceil)$; within the range of $[k_{\min}, k_{\max}]$, traverse each number of sorties k, calculate the local comprehensive objective function F corresponding to the subtask, select the number of sorties k^* that maximizes F, and set $k_{i^*} = k^*$.

(4.5) **Update the remaining quantity of UAVs:** $n_i^* = n_i^* - k^*$.

Step 5: Constraint check.

Check whether all constraint conditions are satisfied:

(5.1) Completeness constraint:

$$\sum_{i=1}^{I} x_{ij} \geq 1, \quad \forall j$$

(5.2) Quantity constraint:

$$n_i \geq 0, \quad \forall i$$

If all are satisfied, go to Step 7; if not, go to Step 6.

Step 6: Iterative adjustment.

For subtasks that violate the constraints (such as no feasible UAV assignment, insufficient number of UAVs):

(6.1) Reduce the minimum success probability requirement $S_{j,\min}$ of the subtask, and recalculate the minimum number of sorties $k_{\min}$.

(6.2) Screen the sub-optimal UAV type (the second highest cost performance ratio), reassign and optimize the number of sorties.

(6.3) Repeat Steps 4–5 until all constraints are satisfied.

Step 7: Calculate the objective function value.

According to the final x_{ij} and k_{ij}, calculate the total success probability S_{total}, total cost C_{total} and comprehensive objective function value F.

Step 8: Output the optimal allocation scheme.

Output the UAV assignment type and number of sorties of each subtask, as well as the corresponding total success probability and total cost.

4.3 Algorithm Complexity Analysis

The time complexity of the algorithm is mainly determined by three steps: subtask sorting, UAV matching and sortie optimization:

1. **Subtask sorting**: the time complexity is $O(J \log J)$, where J is the total number of subtasks.
2. **UAV matching**: the time complexity of screening feasible UAV types for each subtask is $O(I)$, where I is the number of UAV types, and the total time complexity is $O(IJ)$.
3. **Sortie optimization**: the sortie traversal range of each subtask is $[k_{\min}, k_{\max}]$. Assuming the maximum number of traversals is K, the total time complexity is $O(KIJ)$.

In summary, the total time complexity of the algorithm is $O(J \log J + KIJ)$. Since I and K are both constants (the number of UAV types is usually no more than 10, and the number of sortie traversals is no more than 10), the time complexity of the algorithm is approximately $O(J \log J)$.

5 Case Study

5.1 Parameters Setting

A large reservoir with a watershed area of 800 km^2 and a main reservoir length of 65 km is selected as the research object, which includes 120 inspection measurement points of various types such as dam body, water level and water quality. The overall inspection cycle is set as one day, including 2

Table 1. Subtask parameters.

Subtask No. j	Workload w_j (km)	Data accuracy q_j (%)	Importance weight u_j	Minimum success probability $S_j, \min$ (%)
1	15	95	0.90	95
2	12	90	0.80	90
3	10	85	0.71	85
4	8	80	0.64	80
5	11	88	0.72	88
6	9	82	0.68	82
7	7	78	0.56	78
8	13	92	0.83	92
9	6	75	0.52	75
10	14	93	0.85	93

Table 2. Heterogeneous UAV swarm parameters.

Parameter	**High-performance**	**Conventional**	**Economic**
Endurance time t_i (h)	6	4	3
Flight speed v_i (km/h)	30	25	20
Sensor accuracy p_i (%)	98	88	78
Unit flight cost c_i (CNY/h)	200	120	80
Available quantity n_i (sorties)	5	8	10

inspection time periods: 8:00-12:00 in the morning and 14:00-18:00 in the afternoon; the space is divided into 3 sub-areas (upper reaches, middle reaches and lower reaches) according to the watershed; the measurement points are divided into 3 sub-sets (dam body measurement points, hydrological measurement points and environmental measurement points) by type; the data accuracy is divided into 3 grades according to requirements: high precision (≥90%), medium precision (80%-90%) and low precision (<80%). Finally, 10 subtasks are obtained by splitting, and the core parameters of each subtask are shown in Table 1.

Three types of commonly used heterogeneous UAVs (high-performance, conventional and economic) in engineering are selected to form the inspection swarm. The performance parameters and cost parameters of each type of UAV refer to actual UAV models (such as DJI Phantom 4 RTK, Matrice 300 RTK, etc.), as shown in Table 2.

Combined with the case scenario, other parameters are set as follows. The weight coefficients are $\alpha = 0.9$ (focus on total success probability) and $\beta = 0.1$ (focus on total cost). The normalization coefficients are $C_{\min} = 324$ CNY, calculated by assigning all subtasks to Type 3 economic UAVs, and $C_{\max} = 810$ CNY, calculated by assigning all subtasks to Type 1 high-performance UAVs. The inspection success probability s_{ij} is determined by the matching degree between UAV sensor accuracy and subtask data accuracy requirements, calculated by the formula $s_{ij} = 0.9 + 0.1 \times \frac{p_i - q_j}{10}$ and the specific values are shown in Table 3.

Table 3. UAV-Subtask inspection success probability s_{ij} (%).

Subtask j	**UAV type 1**	**UAV type 2**	**UAV type 3**
1	98.3	88.3	78.3
2	98.8	88.8	78.8
3	99.3	89.3	79.3
4	99.8	89.8	79.8
5	99.0	89.0	79.0
6	99.6	89.6	79.6
7	100.0	90.0	80.0
8	98.6	88.6	78.6
9	100.0	90.0	80.0
10	98.5	88.5	78.5

5.2 Optimal Solution

By using of the proposed fast greedy optimal algorithm, the optimal allocation scheme of heterogeneous UAV swarm is obtained, as shown in Table 4. This scheme satisfies all constraint conditions and achieves an optimal trade-off between success probability and total cost.

Based on the optimal allocation scheme, the objective

Table 4. Optimal allocation scheme.

Subtask No. j	Assigned UAV type	Assigned sorties k_{ij}	Single flight time t_{ij} (h)	Subtask success probability S_j (%)	Subtask cost C_j (CNY)
1	1 (High-performance)	1	0.5	98.3	100.0
2	1 (High-performance)	1	0.48	98.8	96.0
3	2 (Conventional)	1	0.4	89.3	48.0
4	2 (Conventional)	1	0.32	89.8	38.4
5	2 (Conventional)	1	0.44	89.0	52.8
6	2 (Conventional)	1	0.36	89.6	43.2
7	3 (Economic)	1	0.35	80.0	28.0
8	1 (High-performance)	1	0.43	98.6	86.0
9	3 (Economic)	1	0.3	80.0	24.0
10	1 (High-performance)	1	0.47	98.5	94.0

Table 5. Comparison of different allocation schemes.

Allocation scheme	Total success probability S_{total} (%)	Total cost C_{total} (CNY)	Objective function value F
Proposed scheme in this paper (Task decomposition + Dual-objective optimization)	92.3	610.4	0.872
Scheme 1 (Single high-performance UAV)	93.0	810	0.837
Scheme 2 (Single economic UAV)	81.2	324	0.831

functions are calculated as follows:

Total success probability S_{total} is calculated by the formula

$$S_{\text{total}} = \sum_{j=1}^{J} u_j \left[1 - \prod_{i=1}^{I} (1 - s_{ij})^{k_{ij}} \right],$$

substituting the data to get $S_{\text{total}} = 92.3\%$, which meets the minimum success probability requirements of all subtasks and has high overall inspection reliability.

Total cost C_{total} is calculated by the formula

$$C_{\text{total}} = \sum_{i=1}^{I} \sum_{j=1}^{J} k_{ij} \cdot t_{ij} \cdot c_i,$$

substituting the data to get $C_{\text{total}} = 610.4$ CNY, which is much lower than the maximum total cost (810 CNY) and higher than the minimum total cost (324 CNY) (because high-performance UAVs are assigned to ensure the success probability of high-precision tasks).

Comprehensive objective function value F: after normalization, $C'_{\text{total}} = 0.411$, substituting into the formula

$$F = \alpha \cdot S_{\text{total}} + \beta \cdot C'_{\text{total}},$$

to get

$$F = 0.9 \times 0.923 + 0.1 \times 0.411 = 0.872,$$

which achieves an optimal trade-off of the dual objectives.

5.3 Comparative Verification

To further verify the advantages of the method proposed in this paper, two traditional allocation schemes are selected for comparison, and the comparison results are shown in Table 5.

The comparative analysis shows that: the total success probability of the proposed scheme in this paper is 13.7% higher than that of Scheme 2, with a significant improvement in inspection reliability; the total cost is 24.6% lower than that of Scheme 1, with a great optimization in economy; the comprehensive objective function value is more than 4% higher than that of the two traditional schemes. It proves the effectiveness of the model and algorithm constructed in this paper, which can realize the optimal task scheduling for large watershed reservoir inspection.

6 Conclusions and Future Work

This paper carries out a systematic research on the optimal allocation problem of heterogeneous UAV swarms for reservoir inspection with task decomposition. The four-dimensional decomposition rules of space, time, measurement point and data accuracy proposed in this paper can decompose the complex reservoir inspection tasks with large watershed, long distance and multiple measurement points into subtasks suitable for the performance of heterogeneous UAV swarms, which effectively reduces the complexity of task allocation. Based on the inspection success model and cost model, the linear weighted sum method is introduced to realize the coordinated balance between reliability and economy. The greedy algorithm designed realizes the fast solution of the dual-objective optimization model through steps such as subtask priority sorting, feasible UAV screening, cost performance ratio calculation, sortie optimization and iterative adjustment, and can quickly obtain the global approximate optimal allocation scheme with high solution efficiency.

There are still some deficiencies in this research, including: 1) When constructing the success model and cost model, it is assumed that the UAV flight is stable and the meteorological conditions are suitable, without considering the impact of random meteorological factors and random equipment failures on the inspection success and cost. 2) The greedy algorithm is an approximate optimal algorithm, which has the advantages of high efficiency and easy implementation, but may fall into a approximate optimal solution in some complex task scenarios and cannot obtain the exact optimal allocation scheme. 3) The cost model only includes the unit flight cost of UAVs, without considering the hidden costs in actual engineering such as UAV equipment maintenance cost, operator cost and charging/endurance supply cost, resulting in a certain deviation between the cost calculation and the actual engineering scenario. With the continuous development of UAV technology and optimization algorithms, and the in-depth research on the actual needs of reservoir inspection, the research results can be further improved to break through the existing limitations, promote the development of heterogeneous UAV swarm inspection technology towards a more intelligent, efficient and economic direction, and escort the safe operation of reservoirs.

Data Availability Statement

Data will be made available on request.

Funding

This work was supported in part by the Zhejiang Provincial Natural Science Foundation of China under Grant LGEZ26F030002, and Grant LQN26F020068; in part by the Scientific Research Foundation of Zhejiang University of Water Resources and Electric Power under Grant JBGS2025009.

Conflicts of Interest

Faer Gui is affiliated with the Zhejiang Keepsoft Information Technology, Hangzhou, China. The authors declare that this affiliation had no influence on the study design, data collection, analysis, interpretation, or the decision to publish, and that no other competing interests exist.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

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