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Research Article

Multi-UAV Cooperative Assisted RSU Data Acquisition Strategy considering Coverage Quality

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The multiple Unmanned Aerial Vehicle (multi-UAV) assisted roadside unit (RSU) data acquisition problem considering the coverage quality is a multiobjective optimization problem, which is a NP-hard problem. Heuristic and hyperheuristic algorithms are effective to solve problems of this type. These algorithms can find the optimal or suboptimal solution in a reasonable time. However, such algorithms still have the problems of low convergence accuracy, slow convergence speed, and being easy to fall into the local optimal solution. In this paper, firstly, according to the specific problem scenarios of roadside unit data collection, minimum cost and maximum coverage models based on task cost and coverage quality are established. Then, to solve the optimization model, combined with the update characteristics of the gray wolf optimization algorithm (GWO) and the whale optimization algorithm (WOA), a hybrid weighted gray wolf and whale optimization algorithm (HWGWOA) is proposed. Finally, to verify the effectiveness of the proposed algorithm, extensive simulation experiments are conducted under four different task acquisition scenarios, and the results are compared with those of genetic algorithm (GA), GWO, and WOA. Simulation results show that the algorithm proposed in this paper not only can get lower task cost and higher coverage quality but also has faster convergence speed and better robustness. Specifically, in terms of task cost, the HWGWOA is about 9.54% lower than the GA, about 7.31% lower than the GWO, and about 5.8% lower than the WOA. In terms of coverage, the HWGWOA is up to about 27.87% higher than the GA, about 15.19% higher than the GWO, and about 9.86% higher than the WOA. Therefore, the algorithm is more suitable for large-scale optimization problems.

1. Introduction

With the development of artificial intelligence, intelligent transportation has become an important research field. In this field, it is crucial to collect road and traffic data. Currently, it mainly relies on roadside units (RSUs) to collect and transmit data to data center. However, in some remote areas, poor areas, or some special areas, data collection and transmission have big challenges [1].

In recent years, unmanned aerial vehicles (UAVs) have been widely used in military and civilian fields because of their high flexibility, low risk, low cost, and easy deployment [2]. At the same time, UAVs are widely used in the field of intelligent transportation, and they play an important role in traffic detection, road patrol, data collection, emergency communications, traffic accident evidence collection, target tracking, and transportation [3]. Compared with traditional mobile sensors, UAVs have faster moving speed, wider deployment range and longer working hours, so they are more suitable for performing various tasks [4–6]. UAV-assisted RSUs have become an effective method of data collection, which have greatly improved the efficiency of data collection [7].

Currently, most UAVs are powered by batteries and cannot complete large-scale tasks independently due to energy consumption constraints. Therefore, it is becoming more and more common for multiple UAVs to perform tasks cooperatively. Collaborative planning is an important way to improve the efficiency of UAVs [8]. At present, most algorithms about UAV task assignment and path planning optimize the following indicators given the number of UAV, such as (1) optimizing the task completion time under the premise of the given number of drones, (2) optimizing the task completion energy consumption under the premise of the given number of drones, and (3) weighing the energy consumption under the premise of the given number of drones and time cost. However, in fact, the optimal number of UAVs to complete tasks is unknown. The optimal number of UAVs is unknown. Assuming there are enough UAVs, it is important to find the best number of UAVs for a given time limit and task set.

In addition, for large-scale data collection scenarios, it will take a long time to collect data from RSUs, and the number of employed UAVs will inevitably increase, which will result in high collection cost. Therefore, in fact, under the constraints of energy consumption and time, as the collection task increases, we cannot collect all RSU data. At this time, the data collection problem is transformed into a sweep coverage problem. At present, for the sweep coverage problem, the coverage rate is generally expressed by the ratio of the number of covered target points to the total number of target points, which is not reasonable in the problem of RSU data collection. In the RSU data collection problem, the RSUs deployed in different locations often collect road and traffic data with different data size and importance at the same time. Therefore, nodes with different importance need different data collection frequency. For example, it is necessary to collect more important and complex data information from RSUs deployed near scenic spots, urban arterial road intersections, and near stations. The RSUs deployed on remote trails carry less important and less data information. To this end, this paper proposes a data collection model based on coverage quality while optimizing time and energy consumption. We define this problem as a minimum cost and maximum coverage problem.

In this paper, the problem of multi-UAV cooperatively assisted roadside unit data acquisition considering coverage quality is regarded as the problem of minimum cost and maximum coverage. We need to dispatch a certain number of UAVs to collect data from RSUs in the target area to achieve the greatest coverage quality with the smallest task cost. This problem is a NP-hard problem, which is an extension of the traveling salesman problem. In order to solve this problem, this paper proposes a hybrid weighted gray wolf whale algorithm with the minimum cost and maximum coverage as the optimization objectives under the constraints of the task and environment.

The main contributions of this article are as follows:

(i) We propose a multi-UAV assisted RSU data collection model that considers the coverage quality, that is, the minimum cost and maximum coverage model. We considered the different importance of different roadside units, assigned weights to the roadside units, and redefined the task coverage. A more suitable coverage calculation model is constructed

(ii) We modeled the problem of multi-UAV assisted RSU data collection. An optimization objective is established to balance task cost and coverage quality. Make the optimization goal more in line with the actual task requirements of the problem. A hybrid weighted gray wolf whale optimization algorithm is proposed to solve the proposed problem and optimize the multi-UAV collaborative mission planning scheme

(iii) This paper simulates mission scenarios of different scales by changing the location and number of roadside units and conducts sufficient simulation and comparison experiments to verify the effectiveness and superiority of the algorithm proposed in this paper. The experimental results show that under different scales of task scenarios, the proposed algorithm achieves lower task cost and higher coverage and has better algorithm stability coverage

The remainder of this paper is organized as follows. Section 2 summarizes the related work. Section 3 describes the requirements and constraints of the problem, explains the meaning of each symbol, and establishes a mathematical model for a specific problem. Section 4 focuses on the algorithm proposed in this paper. Section 5 verifies the effectiveness and superiority of the algorithm through extensive simulations. Finally, Section 6 concludes the paper and proposes some future research direction in this field.

2. Related Work

At present, there are many papers about UAV mission planning. In this section, we will review the literature on cooperative task assignment and path planning for multi-UAVs.

Multi-UAV cooperative task assignment is a typical multiple traveling salesman problem (MTSP), which is a typical NP-hard problem. Many algorithms have been proposed for this problem such as branch and bound method, linear programming, dynamic programming, method based on Voronoi diagram [9], fuzzy logic [10], and differential evolution algorithm [11]. However, when the scale of the problem increases, the computation time will increase exponentially, and the efficiency is low. Therefore, scholars turn to intelligent methods and begin to develop approximate algorithms and heuristic algorithms such as auction algorithm [12, 13], genetic algorithm [14–17], simulated annealing algorithm [18, 19], ant colony algorithm [20–22], particle swarm algorithm [23, 24], and fruit fly optimization algorithm [25]. However, these algorithms were proposed for specific problems, and their universality is poor.

UAV task planning is a problem that finds the optimal path with the minimum cost to complete tasks. These path planning problems are usually solved based on one or several optimization criteria, such as time optimization [3, 6, 15, 18], energy optimization [14, 20], time and energy mix optimization [13, 22, 25–27], and hybrid optimization based on coverage [28]. In terms of time optimization, in Reference [3], a time first immune clonal selection algorithm with optimization modification was proposed to solve the task assignment problem of road patrol. The immune clonal selection algorithm was used to obtain the best sequence of task points, and the time first method was used to divide the sequence of task points. The optimal UAV path was further optimized and modified. Reference [6] solved the problem of path planning for multiple UAVs collecting data from RSUs, and its goal was to find the best time path for multiple UAVs. An improved evolutionary method based on genetic algorithm (GA) and harmony search (HS) was used to solve the problem. Reference [15] pointed out that in the task allocation problem, it is crucial to determine the number of UAVs and find the mission path of each UAV. Based on this idea, the author proposes a collaborative optimization algorithm that combines genetic algorithm and clustering algorithm to solve the task assignment and path planning problems of multiple UAVs for multiple tasks and can find the best UAV when the task time constraints are met. In Reference [18], an effective task allocation and route planning method was proposed to solve the problem of vehicle planning. This method balanced the tasks between UAVs and optimized the task time. According to the number of UAVs, virtual nodes were added to the original model of the vehicle routing problem (VRP), so it is easier to form a solution suitable for the heuristic algorithm. The concept of a universal distance matrix was proposed, which transformed time constraints into space constraints and simplified the planning model. On this basis, a swap judgment simulated annealing (SJSA) algorithm was proposed to improve the generation efficiency of feasible neighbor solutions. In terms of energy optimization, in [14], in order to optimize the UAV energy, the authors describe the UAV path planning problem as a traveling salesman problem. A genetic algorithm is proposed to solve the optimization problem to minimize the energy consumption of the UAV to complete the task. Reference [20] introduced an energy minimization problem of UAV-assisted MEC system and proposed an algorithm based on the ant colony system (ACS) to obtain a high-quality near-optimal solution to this problem, in terms of time and energy mix optimization.

Reference [13] proposed a method based on auction algorithm to allocate dynamic tasks to UAVs, and designed a multilayer cost calculation method considering constraints such as UAV number, time threshold, fuel cost and driving danger to solve the task assignment problem of multi-UAV system. Reference [25] proposed a method of finding the best flight path for UAV to successfully complete the inspection work in oilfield. Firstly, a novel task assignment method was proposed, which included initial task assignment and task assignment with changing tasks to determine the initial task sequence of each UAV, and quickly reschedule the task sequence after the task changes. Then, an improved fruit fly optimization algorithm (ORPFOA) was proposed to solve the path planning problem in the initial task sequence and the new task sequence after task change. In [26], for the solution of task assignment problem, four objectives are simultaneously optimized, namely, maximizing the number of tasks successfully assigned, maximizing task execution benefit, minimizing resource cost and minimizing time cost. A multi-UAV task assignment method based on clone selection algorithm is proposed. In [27], the authors comprehensively consider the problems of minimizing resource consumption and maximizing task revenue during UAV task assignment. On the basis of considering constraints and multiobjective problems, the brute force allocation algorithm, constrained optimization evolutionary algorithm, particle swarm optimization algorithm, and greedy algorithm combined with constrained evolutionary algorithm in the process of UAV task allocation are improved and optimized. And analyze the performance and conclusions of the above four algorithms under the limited UAV task assignment scheme. In terms of coverage-based hybrid optimization, in order to solve the scanning coverage problem in forest fire warning and monitoring, Reference [7] considered the minimum time maximum coverage (MTMC) problem of maximum coverage. The authors propose a heuristic Weighted Targets Sweep Coverage (WTSC) algorithm considering target weights and UAV performance constraints to find the optimal path.

Reference [28] considers finding the optimal path for the UAV to maximize its coverage in the designated area under the time constraints and path feasibility. The problem is modeled as an Epsilon-constraint optimization in which coverage function has to be maximized, considering the constraints on the length and the smoothness of the path. For this purpose, a new genetic path planning algorithm with adaptive operator selection is proposed to solve such a complicated constrained optimization problem. In recent years, autonomous underwater vehicles (UAVs) have been widely used to assist in information collection in ocean development and exploration. In [29], the authors embedded a biologically inspired neural network (BINN) into a self-organizing map (SOM) neural network and divided the tasks into two layers: task assignment and path planning. Utilize BINN to update the weights of SOM winners to realize path planning and efficient navigation of AUVs. Aiming at the problem of information collection in harsh underwater environment, Reference [30] proposed a heterogeneous AUV auxiliary information collection system; the AUV path with low time complexity was obtained by particle swarm algorithm; Additionally, a two-stage joint optimization algorithm based on Lyapunov optimization is constructed to strike a trade-off between energy efficiency and system queue backlog iteratively. In [31], the author considering both the realistic complex underwater acoustic environment and the AUVs energy consumptiona limited service M/G/1 vacation queueing model is constructed for describing and optimizing the age of information(AoI) of the Internet of underwater things (IoUT). Also, a low-computational algorithm is proposed for adaptively adjusting the upper limit of the queuing length formulated and reducing the peak AoI under energy constraints. In order to ensure the efficient operation of UAV, an intelligent mechanism was developed in Reference [32], which considered two main factors, energy consumption and operation time of UAV. Then, three complementary schemes, energy aware UAV (EAUS), delay aware UAV (DAUS), and fair exchange UAV (FTUs), were proposed. These solutions were optimized as linear integer problems (LIP). EAUS solution aims to reduce the energy consumption of UAV, while DAUS solution aims to shorten the operation time of UAV. However, FTUs is a trade-off between energy consumption and task time

As mentioned in Reference [32], for different task type, complexity, constraints and other factors, the optimization objectives of multi-UAV task assignment are different such as minimizing mission time, minimizing energy, and minimizing composite indicator of time and energy. In order to more clearly compare the work done in the existing literature, Table 1 lists the key information of the related literature. In this paper, we study the scan coverage problem of multi-UAV assisted RSU data acquisition. According to the number of UAVs, the task cost and coverage quality are considered comprehensively to find an optimal scheme that can maximize coverage quality and minimize task cost simultaneously. We conclude it as minimum cost maximum coverage model with variable number of UAVs.

3. Problem Formulation and Mathematical Model

A complex urban environment including urban, suburban, and rural areas is considered in this paper. According to the needs of intelligent transportation, it is supposed that several RSUs are deployed in the urban environment to collect road environment and traffic information. In the problem of multi-UAV collaborative assistance RSU data collection, when the number of RSUs is large, it is often impossible to collect data from all RSUs due to the timeliness of data and limited energy of UAVs. Therefore, this paper proposes a minimum cost and maximum coverage model to solve the problem of scanning and coverage. Due to the different locations of RSUs, the importance and size of the data collected by them are different. Therefore, this paper assigns different weight value, a positive integer between one and five, to each RSU according to its importance. The schematic diagram of a multi-UAV cooperatively assisted RSU for data acquisition is depicted in Figure 1.

The problem we considered in this paper can be modeled as a triplet $\{R, U, C\}$, where $R = \{R_1, R_2, \cdots, R_N\}$ is the set of RSUs that are deployed along roads. Each element R_i can also be described as a triplet $\{P_i, D_i, W_i\}$. Symbol P_i is the position coordinates of the i^{th} RSU, D_i is the data size collected by the i^{th} RSU, and W_i is the weight value of the i^{th} RSU. The set of UAVs that are deployed in base station is described by set $U = (U_1, U_2, \cdots, U_K)$. Each element U_j can be described by the same quadruple $\{v, s, L_{\max}, E_{\max}\}$, which means that all UAVs have same flight speed v, transmission speed s, maximum flight distance $L_{\max}$, and energy threshold $E_{\max}$. Symbol C represents the constraints in task assignment. The number of UAVs selected to accomplish the task is k, and the data collection path of the j^{th} UAV is represented as $X_j = [B, R_a, \cdots, R_b, B]$. This problem can be described as a multiple traveling salesman problem. The main symbols and their definitions used in this article are listed in Table 2.

The problem presented above is designing a reasonable scheme of task allocation and path planning for multi-UAVs to collect data from RSUs based on the number, location, data size and weight value of RSUs. To solve this problem, the constraints we considered in this paper are as follows: Firstly, the energy consumption and total flight distance of each UAV to accomplish its tasks cannot exceed its maximum values. Secondly, the number of UAVs used should not exceed the total number of UAVs stay in base station, and each RSU can only be visited by one UAV at most. In addition, UAV should start flying from the base station and finally return to it after finishing data acquisition. These constraints can be expressed as follows:

$$\begin{gathered} E^j \le E_{\max}(j = 1, 2, \cdots, k), \\ L_j \le L_{\max}(j = 1, 2, \cdots, k), \\ k \le K, \\ X_1 \cap X_2 \cap \cdots \cap X_k = B. \end{gathered} \tag{1}$$

In this paper, a mathematical model is established with the objective of optimizing the minimum cost and maximum coverage. Assume that k UAVs are dispatched from the base station to accomplish data collection tasks. When the last UAV returned to base station after finishing data collection, the task is considered as completed. The mission time is defined as the time interval between the take-off time of the first UAV and the return time of the last UAV. Energy consumption is the total energy consumption of k UAVs to accomplish data collection tasks. Coverage is defined as the total weight ratio of RSUs collected by UAVs to all RSUs.

The mission time T^j includes flight time T_f^j and data collection time T_c^j which is described in

$$T^j = T_f^j + T_c^j. \tag{2}$$

The flight time T_f^j and data collection time T_c^j are, respectively, determined by

$$T_f^j = \frac{L_j}{v}, \tag{3}$$

$$T_c^j = \frac{C_{\text{total}}^j}{s}. \tag{4}$$

The flying distance L_j and total data size C_j are calculated using

$$L_j = \sum D_{X_j}, \tag{5}$$

$$C_j = \sum C_{X_j}. \tag{6}$$

The total energy consumption of UAVs to accomplish tasks includes flight energy consumption, hovering energy consumption, and data transmission energy consumption. Compared with flight energy consumption and hovering energy consumption, data transmission energy consumption is negligible. Therefore, the total energy consumption of UAV U_j is expressed as follows:

$$E_j = E_f^j + E_h^j. \tag{7}$$

Table 1: The key information of the related literature.

Reference	Application field	Optimization objective	Algorithm of UAVs	Number type	Overlay
[3]	Road patrol	Time	Immune clonal selection algorithm (ICSA) and time-priority method	Fixed	All
[6]	RSU data collection	Time	Genetic algorithm (GA) and harmony search (HS)	Fixed	All
[15]	Task planning	Time	GA and cluster algorithm	Variable	All
[18]	Task planning	Time	Swap-and-judge simulated annealing (SJSA)	Fixed	All
[14]	Monitoring wildfires in remote areas	Energy	Hybrid gray wolf optimization (HGWO)	Fixed	All
[20]	Data collection in mobile edge computing	Energy	Ant colony system (ACS)	Fixed	All
[22]	Reconnaissance task allocation	Time and energy	Grouping ant colony optimization algorithm (GACO)	Fixed	All
[25]	Oilfield inspection	Time	An improved fruit fly optimization algorithm (ORPFOA)	Fixed	All
[26]	Task allocation	Time and energy	Clone selection algorithm (CSA)	Fixed	All
[27]	Task allocation	Energy and revenue	Violence allocation algorithm; constraint optimization evolutionary algorithm; PSO algorithm; greedy algorithm combined with a constraint evolutionary algorithm	Fixed	All
[7]	Forest fire early warning and monitoring	Time and coverage	Heuristic algorithm weighted targets sweep coverage (WTSC)	Fixed	Partial
[28]	Coverage-based path planning (CBPP) problem	Coverage rate	Genetic algorithm with adaptive operator selection	Fixed	Partial
In this paper	RSU data collection	Time, energy, and coverage	Hybrid weighted gray wolf and whale optimization algorithm (HWGWOA)	Variable	Partial

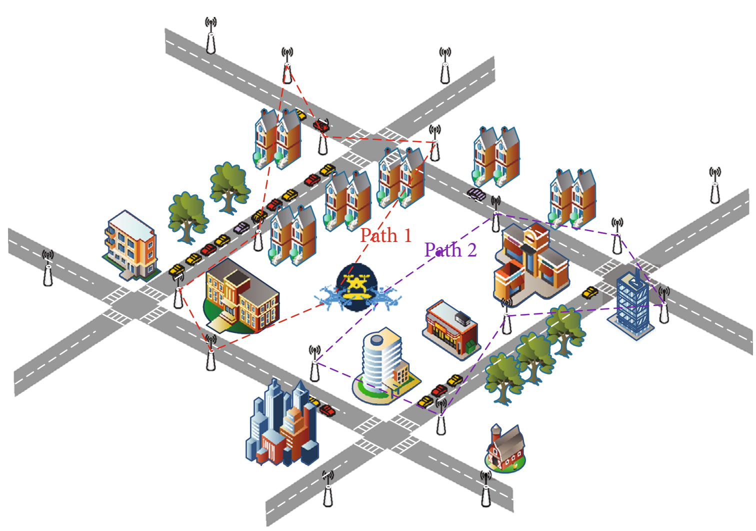


Figure 1: Multi-UAV cooperatively assisted RSUs for data collection.

Table 2: Symbols and their definitions used in this paper.

Parameters	Definition
N	Number of RSUs
K	Number of UAV base stations
k	Number of UAVs selected
$B(x_B, y_B)$	Base station coordinates
$R_i(x_i, y_i)$	Coordinates of the RSU R_i
C_i	Size of data collected by RSU R_i
D_{ij}	Distance from RSU R_i to RSU R_j
$L_{\max}$	Maximum flying distance of UAV
$E_{\max}$	Energy consumption threshold of UAV
v	Flying speed of UAV
s	Data transmission rate of UAV
$X_j = [B, R_a, \cdots, R_b, B]$	Data collection path of UAV U_j
T_f^j	Flight time of UAV U_j
T_c^j	Data collection time of UAV U_j
T^j	Task time of UAV U_j
L_j	Flying distance of UAV U_j
C_{total}^j	Size of data collected by UAV U_j
E_f^j	Flight energy consumption of UAV U_j
E_h^j	Hovering energy consumption of UAV U_j
E^j	Task energy consumption of UAV U_j
P_f	Flying power of UAV U_j
P_h	Hovering power of UAV U_j
W_i	Weight of RSU R_i
F	Task cost
W	Coverage quality
P	Coverage

The calculation of flight energy consumption and hovering energy consumption is as follows:

$$\begin{aligned} E_f^j &= L_j \times P_f, \\ E_h^j &= T_c^j \times P_h. \end{aligned} \tag{8}$$

The flight power P_f and hovering power P_h are specific parameters of UAV, which can be found in its handbook.

In this paper, the optimization objective is the weighted sum of maximum task time and total task energy consumption, which is expressed as follows:

$$F = \gamma \sum_{j=1}^{k} E_j + (1-\gamma) \max \left[T^1, T^2, \cdots, T^{k-1}, T^k\right]. \tag{9}$$

Here, $\gamma \in [0, 1]$ is the weight coefficient reflecting the importance of task energy consumption in the entire data collection task.

In this paper, the problem we considered is a problem of incomplete coverage, which means that not all RSUs must be visited by UAVs, However, due to the large number of UAV in this scenario. Therefore, the coverage ratio is another important optimization indicator, which is calculated as follows:

$$P = \frac{W}{\sum_{i=1}^{N} W_i}. \tag{10}$$

The coverage quality W can be calculated by

$$W = \sum_{i=1}^{N} (X_i W_i). \tag{11}$$

Here, X_i is a binary variable, which is determined by

$$X_i = \begin{cases} 1, \text{The UAV passes by the } R_i, \\ 0, \text{other}. \end{cases} \tag{12}$$

The main goal of this paper is to achieve maximum coverage with minimal task energy consumption in the shortest task time. When the weights of all RSUs are known, the total weight is a constant. Therefore, the coverage ratio can be substituted by the coverage quality; then, the optimization objectives are minimizing F and maximizing the coverage quality W simultaneously. This problem is a typical multiobjective optimization problem.

To transform the multiobjective optimization problem to a single objective optimization problem, a utility function Y as described in (13) is proposed to represent the total benefit of the task.

$$Y = \lambda F - (1-\lambda) W. \tag{13}$$

Here, $\lambda \in [0, 1]$ is a weight coefficient, which reflects the importance of the task cost in the entire data collection task, and its value will be given in the simulation experiment part. Finally, the optimization problem in this paper is written as

$$\begin{gathered} \min\ (Y) \\ \text{S.t.} \\ C_1 : E^j \le E_{\max} (j = 1, 2, \cdots, k) \\ C_2 : L_j \le L_{\max} (j = 1, 2, \cdots, k) \\ C_3 : k \le K \\ C_4 : X_1 \cap X_2 \cap \cdots \cap X_k = B. \end{gathered} \tag{14}$$

Constraint C_1 ensures that each UAV has enough energy to complete its missions. Constraint C_2 ensures that the flight distance of each UAV does not exceed its maximum flight distance. Constraint C_3 ensures that the number of

UAVs selected does not exceed the number of UAVs in the base station. Constraint C_4 ensures that the data of each RSU is collected by only one UAV.

The solution of multi-UAV coassisted RSU data collection is the grouping and combination sorting of some RSUs in the target area, so the problem is a combinatorial optimization problem. Combinatorial optimization problems are NP-hard problems. When the problem become large, it is difficult to find the optimal solution in a short time. In addition, the strong coupling of multi-UAV collaborative task assignment also increases the difficulty of solving the problem. Therefore, an effective solution for multi-UAV coassisted RSU data collection is to design heuristic or hyperheuristic algorithms to find the optimal solution or suboptimal solution in a reasonable time.

4. Algorithm Design

In order to solve the problems of slow convergence speed, low convergence accuracy, and being easy to fall into local optimal solution of bionic learning algorithm in solving combinatorial optimization problems, in this paper, we propose an improved hybrid weighted gray wolf and whale optimization algorithm to optimize the task assignment scheme of multiple UAVs. Firstly, the grey wolf optimization algorithm (GWO) [33] is improved and further mixed with the whale optimization algorithm (WOA) [34], which is called hybrid weighted grey wolf and whale optimization algorithm (HWGWOA). The specific improvement ideas of the algorithm are as follows.

(a) Tent map initialization

Bionic learning algorithm uses random initialization to generate initial population, each individual in the population is a feasible solution, and then the solution is updated to the optimal solution or suboptimal solution step by step through iteration. It can be seen that the quality of the initial solution will greatly affect the convergence speed and final results of the algorithm. However, random initialization can't guarantee the diversity and ergodicity of the initial solution, especially when the population size is small; it will lead to uneven distribution of the initial solution, which is not conducive to the updating and optimization process of the algorithm.

In order to ensure the uniformity and diversity of the initial feasible solution in the solution space, a tent map [35] is used to initialize the population. The chaotic sequence has the characteristics of inner randomness, ergodicity, and boundedness, but the ergodic uniformity of chaotic sequence generated by different maps is different, which will have different effects on the optimization speed of the algorithm. At present, most of the research uses the chaotic sequence generated by logistic mapping. However, the uniformity of the chaotic sequence generated by logistic mapping is poor, and most of the values are in the interval [0, 0.1] and [0.9, 1] [36]. Tent mapping has a simple structure, better ergodic uniformity, and faster iteration speed, and the chaotic sequences generated by it are evenly distributed in [0, 1]. Therefore, in this paper, tent mapping is selected to initialize the population. The mathematical expression of tent mapping is

$$x(n+1) = \begin{cases} \dfrac{x_n}{a}\, x_n \in [0, a), \\ \dfrac{1 - x_n}{(1-a)} x_n \in [a, 1]. \end{cases} \tag{15}$$

(b) Weighted update mechanism

The GWO algorithm uses the three solutions, alpha (α), beta (β), and delta (δ), with the highest fitness value to guide other individuals to update towards the optimal solution. In the original GWO algorithm, the guidance strength of the three best solutions is the same, which will make the algorithm easily fall into the local optimal solution area. In order to increase the diversity and randomness of the updates, we use the weighted update mechanism. Each update randomly generates three weight coefficients added to the three solutions.

$$\begin{cases} D_\alpha = |C_1 X_\alpha - X_t| \\ D_\beta = |C_2 X_\beta - X_t|, \\ D_\delta = |C_3 X_\delta - X_t| \end{cases} \tag{16}$$

$$\begin{cases} X_1 = X_\alpha - A_1 \cdot D_\alpha \\ X_2 = X_\beta - A_2 \cdot D_\beta . \\ X_3 = X_\delta - A_3 \cdot D_\delta \end{cases} \tag{17}$$

$$X_{t+1} = \frac{(J_1 X_1 + J_2 X_2 + J_3 X_3)}{3}, \tag{18}$$

where equations (16) and (17) define the update direction and step length of other individuals in the wolf pack towards α, β, and δ. J_1, J_2, and J_3 are weight coefficients, and they are calculated by

$$J_1 = \frac{j_1}{(j_1 + j_2 + j_3)}, \tag{19}$$

$$J_2 = \frac{j_2}{(j_1 + j_2 + j_3)}, \tag{20}$$

$$J_3 = \frac{j_3}{(j_1 + j_2 + j_3)}, \tag{21}$$

where j_1, j_2, and j_3 are random numbers of [0, 1].

(c) Hybrid spiral renewal mechanism

In this paper, we propose a new hybrid algorithm composed of the improved GWO algorithm and WOA. In this hybrid algorithm, the WOA is adopted at the exploration stage due to its good global search ability, which is achieved by its logarithmic spiral update. In addition, the location of the best solution found by the GWO algorithm is replaced by the location of the whale. The

Input: R,U,C
Output: Y,X^*
Initialize the population:$X = (X_1, X_2,\cdots,X_m)$;
Initialize the parameter: a,A,C,l,T , $p,t = 0$;
Calculate the fitness of each search agent;
$X_t^* = X_\alpha$ =the best search agent;
X_β =the Second best search agent;
X_δ = the Third best search agent;
While $(t < T)$
  For (every search member)
    Update a,A,C,l,T and p;
    If1$(|A| \le 1)$
      If2$(p < 0.5)$
        Update the position of the current search agent by the Equation (24);
      Else if2$(p \ge 0.5)$
        Update the position of the present search agent by the Equations (25);
      End if2
    Else if1$(|A| > 1)$
      Select a random search agent X_{rand}
      Update the position of the current search agent by the Equation (26);
    End if1
  End for
  Calculate the fitness of each search agent;
  Update X^*, X_α,X_β and X_δ ;
  t = t +1;
End while
Return X^* ;

Algorithm 1: HWGWOA.

location of the whale is the same as that of the gray wolf, but it can quickly move to the optimal solution. The WOA guides the wolves to converge to the optimal solution, and reduce the calculation time.

In a word, combining the best characteristics of GWO algorithm and WOA makes the probability of finding the global optimal solution higher, and the algorithm stagnation or falling into local optimization is avoided. The HWGWOA combines the advantages of the GWO algorithm at the exploitation stage and the WOA at the exploration stage to obtain the global optimal solution. The mathematical model of HWGWOA is as follows:

According to the hierarchical system, the GWO algorithm preserves three solutions with the highest fitness value in each iteration, which are named α, β, and δ, respectively. In order to improve the convergence performance of the GWO algorithm, the spiral update equation of the WOA is used to update the positions of alpha, beta, and delta as described by

$$\begin{cases} D_\alpha = |C_1 \cdot X_\alpha - Q| \\ D_\beta = |C_2 \cdot X_\beta - Q|, \\ D_\delta = |C_3 \cdot X_\delta - Q| \end{cases} \tag{22}$$

$$Q = X_t + D' e^{bl} \cos(2\pi l), \tag{23}$$

where $D' = |X_t^* - X_t|$ denotes the distance from an individual to the prey, b is a constant that defines the shape of the logarithmic helix, and l is a random number in [-1, 1].

To sum up, the updating mechanism of HWGWOA is described by (24)–(31).

$$X_{t+1} = X_t^* - A \cdot D|\mathrm{A}| \le 1P < 0.5, \tag{24}$$

$$X_{t+1} = \frac{(J_1 X_1 + J_2 X_2 + J_3 X_3)}{3} |A| \le 1p \ge 0.5, \tag{25}$$

$$X_{t+1} = X_{\text{rand}} - A \cdot D_{\text{rand}}|\mathrm{A}| > 1, \tag{26}$$

where

$$D = |C \cdot X_t^* - X_t|, \tag{27}$$

$$A = 2 \times a \cdot r_1 - a, \tag{28}$$

$$C = 2 \times r_2, \tag{29}$$

$$a = 2 \times \cos\left(\frac{\pi}{2} \times \frac{t}{T}\right), \tag{30}$$

$$D_{\text{rand}} = |C \cdot X_{\text{rand}} - X_t|, \tag{31}$$

where t is the current number of iterations, T is the maximum number of iterations, p,r_1,r_2 are random numbers in [0, 1], X_t is the current position of a individual, and X_t^* is the optimal solution of the current iteration.

Table 3: The main parameters symbols in this paper.

λ		0.1	0.3	0.5	0.7	0.9
$N = 30$	Task cost coverage rate	45.96 0.90	42.70 0.97	43.80 0.93	43.65 0.95	43.84 0.89
$N = 50$	Task cost coverage rate	63.70 0.93	57.36 0.83	53.94 0.91	55.64 0.92	60.20 0.88
$N = 70$	Task cost coverage rate	80.93 0.77	77.52 0.79	70.51 0.79	75.73 0.72	77.95 0.69
$N = 100$	Task cost coverage rate	95.65 0.68	91.95 0.72	87.10 0.76	82.53 0.78	94.96 0.69

Table 4: Task cost and coverage rate under different scenarios.

RSU number	UAV number	Total weight	Task cost	Coverage rate
30	2	78	51.33	0.86
	3		42.81	0.93
	4		43.80	0.94
	5		45.98	0.97
50	2	127	68.17	0.79
	3		63.01	0.84
	4		53.94	0.91
	5		57.47	0.93
70	2	180	91.88	0.67
	3		78.97	0.72
	4		70.51	0.80
	5		72.83	0.86
100	2	226	117.86	0.64
	3		96.87	0.69
	4		87.10	0.73
	5		79.92	0.78

In the whole iterative process, by controlling the parameters of a, A, C, l, and p, the algorithm makes full global search at the early stage and accelerates convergence at the later stage. The pseudocode of the HWGWOA is shown in Algorithm 1.

In the HWGWOA, we set the number of populations as N, taking one iteration as an example. N calculations are needed to initialize the population, calculate the fitness of each individual, and update the individual position. The first three individuals selected by us need $3N - 3$ calculations at most. The update parameter is constant time, and the calculation in the iterative process is serial. Therefore, the time complexity of the algorithm is $O(N)$.

5. Simulation and Result Analysis

In this section, simulation results are provided to evaluate the performance of the HWGWOA. Specifically, we compare the HWGWOA with the genetic algorithm (GA) [17], GWO [37], and WOA [38]. As a classical algorithm to solve TSP and MTSP, the GA has good stability. GWO algorithm and WOA, as two bionic learning algorithms proposed in recent years, show good performance in solving optimization problems and are also widely used in various optimization problems. All simulations in this section are carried out in MATLAB. All experimental data are rounded to 2 decimal places. The detailed experimental results are as follows.

(A) Simulation model

The parameters in the simulation are set as follows. We consider a 10 km Ã-10 km urban area and randomly deploy multiple RSUs. Four different scenarios are chosen for simulation experiments, whose number of RSUs is set to 30, 50, 70, and 100, respectively. The total number of UAVs in the base station is 5. The base station location of UAV is $B(1, 1)$. It is assumed that the configuration of each UAV is the same; that is, the UAV flies at a constant speed of 60 km/h when performing tasks, and the data transmission speed of UAV is 1.5 mbps/s.

(B) HWGWOA performance evaluation

Here, we study the influence of system parameters on the performance of HWGWOA. In order to achieve the goal of

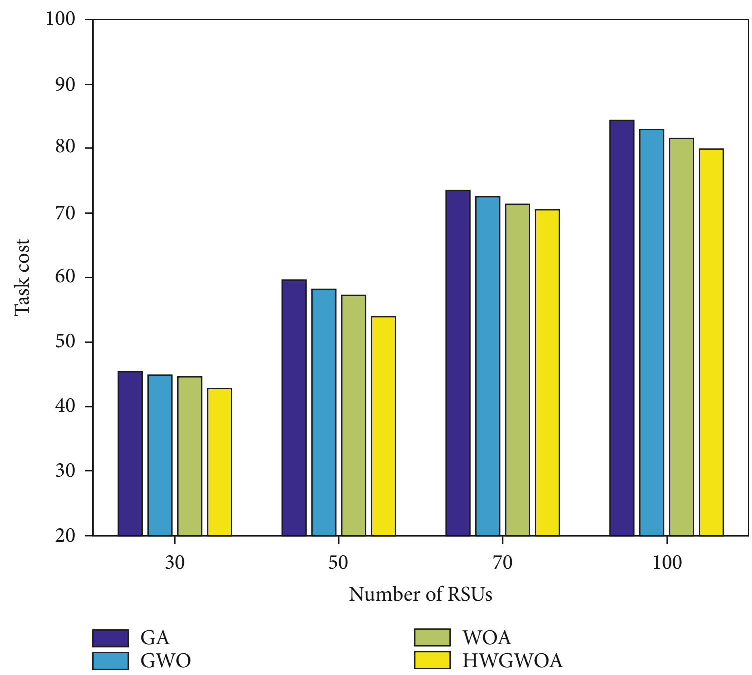


Figure 2: Task cost under different numbers of RSUs.

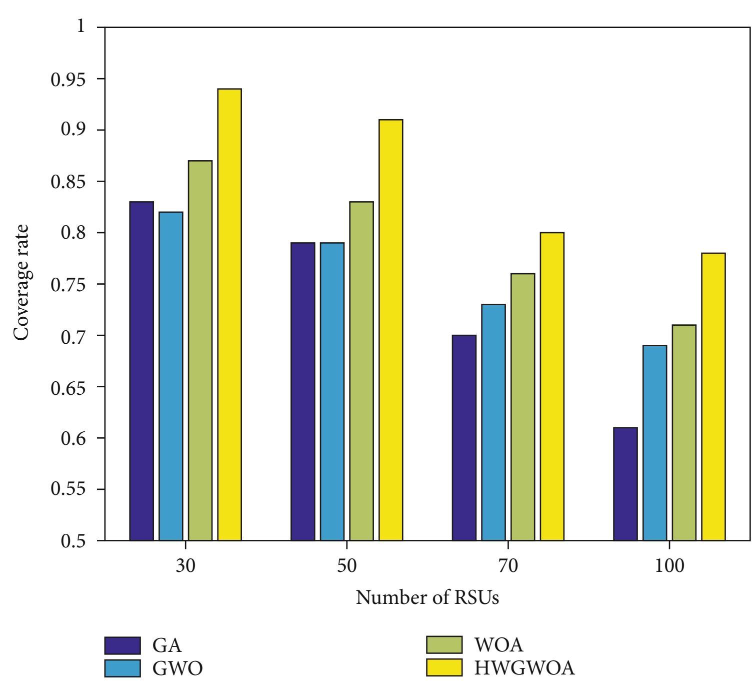
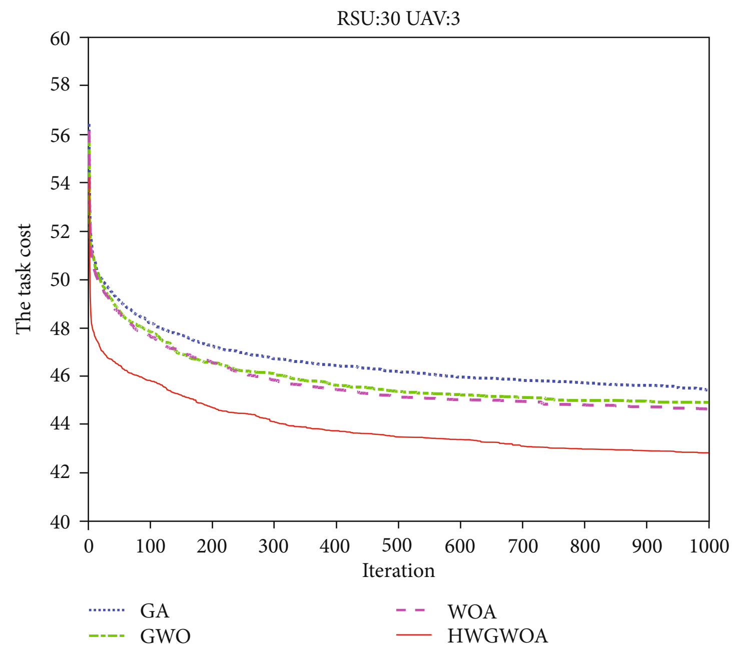


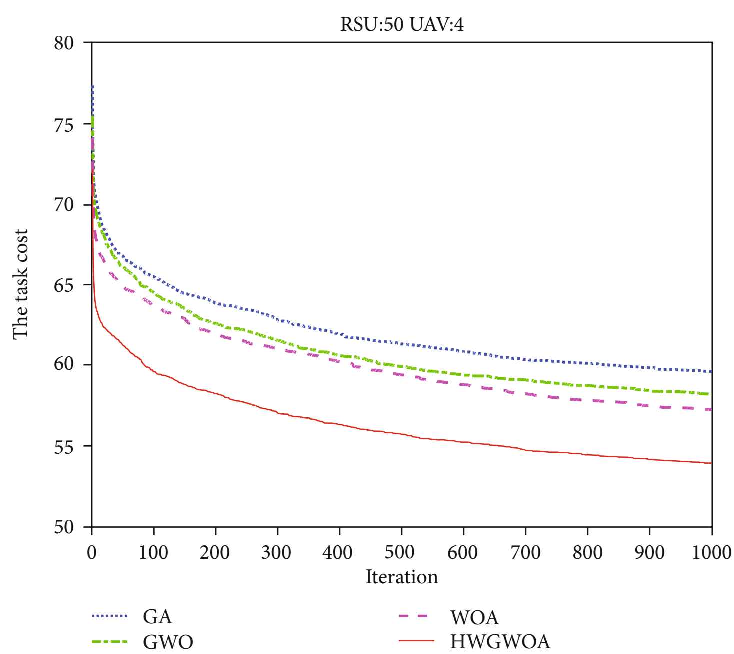
Figure 3: Coverage rate under different numbers of RSUs.

minimum cost and maximum coverage, the weight of task cost and coverage quality should be considered in task planning. Here, we assign equal weights to task time and task energy consumption in task cost; that is, γ in formula (9) is fixed at 0.5.

In formula (13), we use the adjustment parameter γ to balance the weight between task cost and coverage quality. We adjust it from 0.1 to 0.9 and set the number of UAVs to 4 for simulation. Algorithm 1 shows the change of task cost and coverage rate with parameter γ when the number of RSUs is 30, 50, 70, and 100, respectively. Because the algorithm uses random initialization, in order to better show the convergence effect, this paper uses the average of 30 convergence results as the convergence value.



(a)



(b)

Figure 4: Continued.

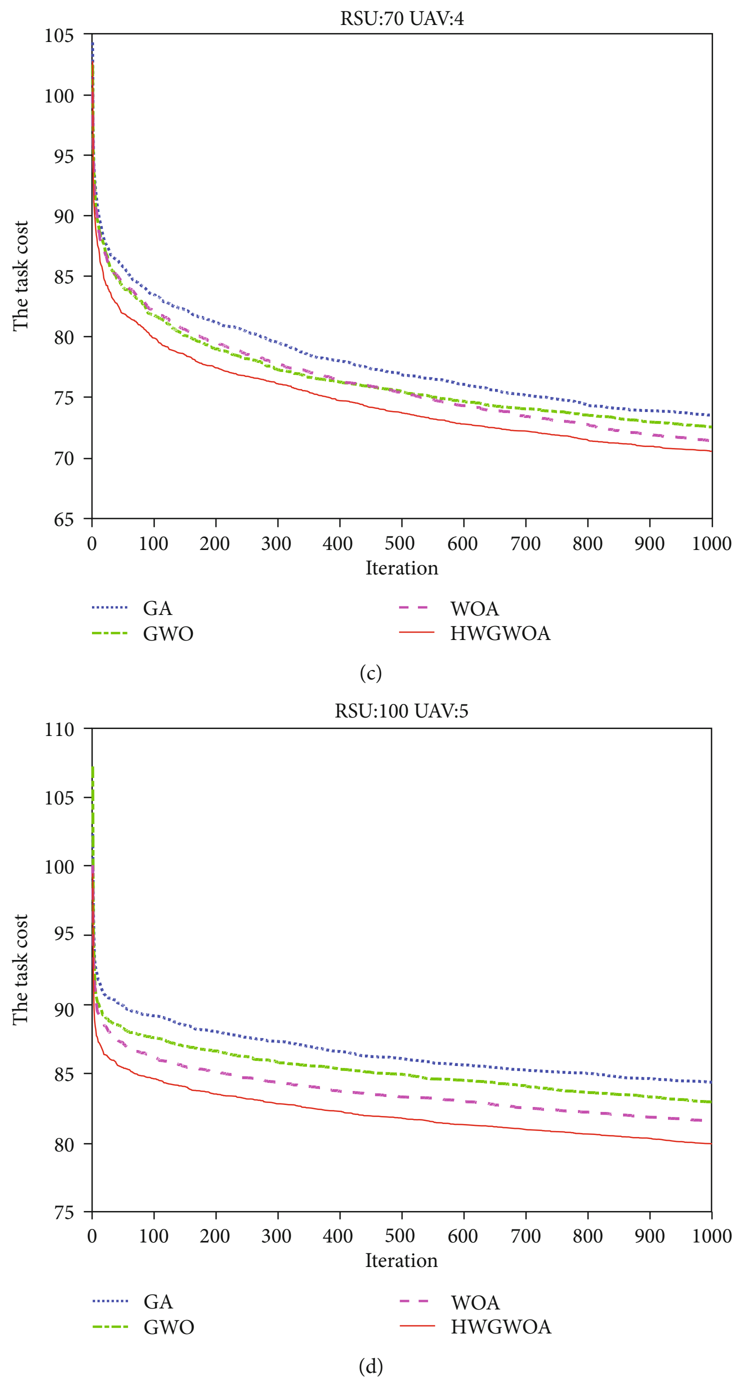


Figure 4: Convergence results of the four algorithms.

Simulation results show that the algorithm is better when γ is between 0.3 and 0.7, as shown in Table 3; we can get lower acquisition cost and higher coverage quality.

Then, we investigate the optimal number of UAVs with different numbers of RSUs. When the parameter γ is set to 0.5, that is, the task cost and the coverage quality weight are equal, the change of task cost and coverage rate with the number of RSUs and UAVs is tested. The number of UAVs is changed from 2 to 5, and the numbers of RSUs are 30, 50, 70, and 100, respectively. Similarly, the average of 30 convergence results is used as the convergence value. The total cost of each case is shown in Table 4.

It can be seen from Algorithm 1 that when the number of RSUs is 30 and the number of UAVs is 3, the total cost is the smallest and the coverage rate is high. When two UAVs are selected, each UAV needs to collect more RSUs, which makes the task cost maximum. Due to the constraint of energy consumption, the path will ignore more nodes, resulting in lower coverage rate. However, when there are more UAVs, individual UAVs will collect less RSUs and

Table 5: Stability comparison of the four algorithms.

		GA	GWO	WOA	HWGWOA
Scene 1	Worst	47.82	47.40	47.81	45.58
	Best	44.40	43.73	43.83	41.90
	Mean	45.41	44.89	44.62	42.81
	Std	0.77	1.02	0.99	0.84
Scene 2	Worst	61.46	62.17	60.56	55.71
	Best	57.92	56.25	54.93	51.82
	Mean	59.62	58.19	57.26	53.94
	Std	0.96	1.36	1.51	1.04
Scene 3	Worst	76.25	76.41	75.89	74.49
	Best	70.95	69.23	67.36	67.51
	Mean	73.51	72.53	71.37	70.51
	Std	1.43	2.14	2.10	1.69
Scene 4	Worst	87.29	85.93	84.45	82.41
	Best	81.70	78.96	78.87	77.68
	Mean	84.37	82.95	81.57	79.92
	Std	1.38	1.58	1.49	1.18

return to the base station, which greatly increases the energy consumption, resulting in higher task cost, but lower coverage rate. Similarly, when the number of RSUs is 50 and the number of UAVs is 4, the minimum task cost and high coverage rate will be obtained. When the number of RSUs is 70 and the number of UAVs is 4, the mission cost is the lowest and the coverage rate is higher. When the number of RSUs is 100 and the number of UAVs is 5, the mission cost is the lowest and the coverage rate is the highest. Therefore, with the increase in the number of tasks, increasing the number of UAVs appropriately can get lower task cost and higher coverage.

(C) Algorithm convergence comparison

In order to verify the performance of the algorithm, this paper compares the task cost and coverage of genetic algorithm, gray wolf optimization algorithm, and whale optimization algorithm for multi-UAV coassisted RSU data collection. The convergence of the four algorithms in 1000 iterations was tested in the following four scenarios: (1) 30 RSUs and 3 UAVs, (2) 50 RSUs and 4 UAVs, (3) 70 RSUs and 4 UAVs, and (4) 100 RSUs and 5 UAVs. Similarly, the average value of 30 simulations of the algorithm is used as the convergence result. The task cost comparison is shown in Figure 2, and the coverage comparison is shown in Figure 3.

As shown in Figures 2 and 3, HWGWOA achieves lower task cost and higher coverage in the above four scenarios. Specifically, as for task cost, HWGWOA is 9.54% lower than the genetic algorithm, 7.31% lower than the gray wolf algorithm, and 5.8% lower than the whale algorithm; in terms of coverage, HWGWOA is 27.87% higher than the genetic algorithm, 15.19% higher than the gray wolf algorithm, and 9.86% higher than the whale algorithm. In a word, HWGWOA has low task cost compared with the other three algorithms, and it can get more coverage. When the number of RSUs increases, this advantage is more obvious. In order to more intuitively compare the convergence speed and convergence results of the four algorithms, the convergence trends of task cost of the four algorithms in four scenarios are shown in Figure 4.

As shown in Figure 4, in the four scenarios, the HWGWOA acquires a lower task cost and a faster convergence speed. When the task scale is small, this advantage is more obvious. As the task scale increases, it becomes more difficult to solve the problem, and the advantage of the HWGWOA decreases a little.

(D) Stability comparison of four algorithms

Robustness is an important index to evaluate the performance of this kind random search algorithm. Therefore, the robustness of four algorithms is tested in this section. To this end, each algorithm runs for 30 times, and the optimal solution, the worst solution, the average solution, and the variance of the task cost are recorded as shown in Table 5.

As shown in Table 4, the convergence accuracy of genetic algorithm is the worst, but the variance is small, that is, the robustness of the algorithm is good; the convergence accuracy and stability of gray wolf optimization algorithm and whale optimization algorithm are general; HWGWOA is better than the gray wolf optimization algorithm and whale optimization algorithm in convergence accuracy and robustness. When the task scale is small, the robustness is slightly worse than that of the genetic algorithm; with the task size increasing, the robustness of HWGWOA is better when the number of RSUs reaches 100 with the increase in modulus. It can be seen that HWGWOA has better convergence speed and accuracy than the other three algorithms in solving the data acquisition problem of multi-UAV coassisted RSU, and it also has better algorithm robustness, which is more suitable for solving large-scale optimization problems.

6. Conclusion and Further Work

This paper investigated the data acquisition of multi-UAV coassisted RSU in a large-scale scene. First of all, according to the physical constraints and collaborative constraints of UAV, considering the two factors of mission cost and mission coverage quality, a maximum cost minimum coverage model was proposed to seek the solution to obtain the maximum coverage benefit under the premise of minimum mission cost. Then, the HWGWOA was proposed for UAV mission planning. Finally, the HWGWOA was compared with the genetic algorithm, gray wolf optimization algorithm, and whale optimization algorithm. The experimental results show that the HWGWOA has faster convergence speed, better stability, and higher convergence accuracy, and it is more suitable for large-scale optimization problems. In the future work, we are committed to further research from the following aspects: on the one hand, we will solve the real-time replanning problem of multi-UAV cooperative task planning according to the actual constraints; on the other hand, we will consider the multi-UAV cooperative task planning problem under rechargeable conditions.

Data Availability

The raw/processed data required to reproduce these findings cannot be shared at this time as the data also forms part of an ongoing study.

Additional Points

This article is a further expansion based on conference papers. Conference papers consider a smaller task environment and fewer roadside units. In the conference papers, the task distribution and path planning schemes are mainly formulated according to the task set to realize the complete collection of roadside unit data. On this basis, this article considers more realistic large-scale scenarios. In a large-scale data collection scenario, it will take a long time to collect data from all roadside units. Therefore, the number of drones selected will inevitably increase, which will result in high collection costs. In actual scenarios, there are energy consumption and time constraints. As the collection tasks increase, we cannot collect all roadside unit data. At this time, we need to perform partial collection, and the problem is transformed into a scan coverage problem, that is, an incomplete coverage problem. At present, for the scan coverage problem, the coverage rate is generally expressed by the ratio of the number of target points covered to the total number of target points. This is not reasonable in the data collection problem of the roadside unit. In the problem of roadside unit data collection, roadside units deployed in different locations often collect road and traffic information of different data sizes and different degrees of importance in the same time period. This leads to different data collection needs for each node. For example, roadside units deployed near scenic spots, urban main road intersections, near stations, etc., will collect more important and complex data information. On the contrary, a roadside unit deployed on a remote trail will carry less important and less data information. Therefore, this paper proposes a data collection model based on coverage quality while optimizing time and energy consumption. We define it as the minimum cost and maximum coverage problem.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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