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Trajectory Planning for Reconnaissance Mission Based on Fair-Energy UAVs Cooperation

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ABSTRACT Unmanned aerial vehicles (UAVs) have recently received growing popularity in reconnaissance missions due to their many advantages, such as high mobility, flexible deployment, and low operational costs. In this paper, we investigate how the UAVs should optimally exploit its mobility via trajectory planning to achieve the fairness of energy consumption with communication, hovering, and motion energy consumption in consideration. Most of the current works only consider motion energy consumption; however, communication and hovering energy consumption cannot be ignored. We first formulate this problem as a min–max tour cover problem that has been proved to be NP-hard. Then, a heuristic algorithm is proposed to minimize the maximum energy consumption of the reconnaissance UAVs by planning the trajectories. Next, to guarantee the fairness of energy consumption under scenarios with strict and firm energy requirements, we propose an approximation algorithm that can achieve an approximation ratio of 2.5. Finally, the extensive simulations are conducted under different settings to evaluate the performance of our proposed algorithms. The results show that the algorithms can improve the fairness of energy consumption and reduce the maximum energy consumption compared with other algorithms.

INDEX TERMS Unmanned aerial vehicles (UAVs), fair energy consumption, trajectory planning, heuristic algorithm, approximation algorithm.

I. INTRODUCTION

Recently, Unmanned Aerial Vehicles (UAVs) have attracted increasing attention in diverse domains such as military, civilian, and commercial domains. Due to their high mobility and maneuverability, deployment flexibility as well as cost-effectiveness, UAVs are used in many applications to provide outperforming solutions [1], [2]. For example, there has been a fast-growing interest in utilizing UAVs as aerial base stations to help enhance the coverage and performance of communication networks in various scenarios, and provide network service for remote areas [3], [4]. In addition, UAVs are extensively used in monitoring applications, such as forest, wildlife, agricultural and water quality monitoring [5]. Furthermore, in the military field, driven by the continuous cost reduction and the device miniaturization of communication equipment, it is also a safer and more economical choice to use UAVs to execute reconnaissance missions than manned aircraft [6]. To this end, GPS, sensors and high-resolution cameras can be installed on UAVs to guarantee better area reconnaissance than ground wireless sensor networks [7].

Compared with a single UAV, multi-UAV system can collaboratively complete reconnaissance missions more economically and efficiently [8]. As shown in Fig. 1, according to the participation way of multi-UAV, there are mainly two reconnaissance scenarios. As shown in Fig. 1(a), in the

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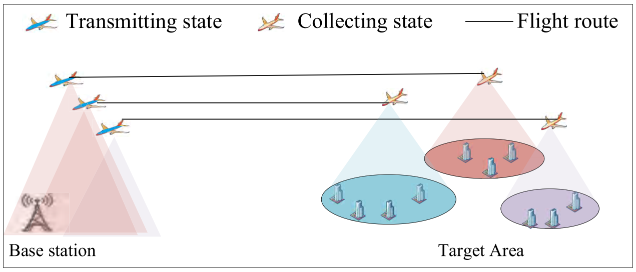
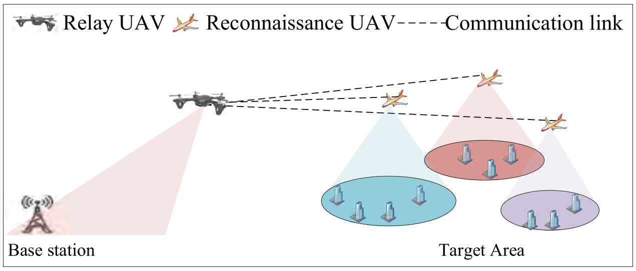


(a) Reconnaissance without UAV relay



(b) Reconnaissance with UAV relay

FIGURE 1. Reconnaissance scenarios of UAVs.

reconnaissance scenario without UAV relay, there is only one type of UAVs which have two states. The UAVs collect information from the target area and then fly to the base station to upload collected information. For the former, the UAVs are in collecting state. For the latter, the UAVs are in transmitting state. However, in a large-area environment, where the target area is often far from the base station, energy may be exhausted before UAVs carry information back to the base station. As shown in Fig. 1(b), the reconnaissance UAVs collect the information from the target area, but they only need to transmit the information to the relay UAV rather than the base station. In reconnaissance mission, using the relay UAV is an effective technique for improving the communication reliability and prolonging the lifetime of multi-UAV [9], [10]. In this paper, we focus on the scenario where the relay UAV is used in the reconnaissance mission.

Under this scenario, the total energy consumption of a reconnaissance UAV includes three parts, *i.e.* motion, hovering and communication energy consumption. Since the reconnaissance UAVs transmit the information to the relay UAV instead of the base station, they can save the motion energy consumed by the UAVs flying to the base station. Each reconnaissance UAV is responsible for different target points. Once the energy of an UAV is exhausted, the whole mission will not be completed. Therefore, the problem of fair energy consumption among the UAVs is critical for the success of the whole reconnaissance mission. In order to enhance mission success probability and achieve the fairness of energy consumption, we pursue to minimize the maximum energy consumption of reconnaissance UAVs by planning their trajectories.

There have been many works on how to minimize the total energy consumption of all nodes in wireless networks [11]–[16]. However, they rarely discuss the problem of fair energy consumption. Although some current works study the fairness of energy consumption [17]–[22], they don't consider the point's cost which represents the communication and hovering energy consumption in the reconnaissance mission. On the one hand, the hovering and communication energy consumed by reconnaissance UAVs cannot be ignored and contributes significantly to the total energy consumption. On the other hand, considering the energy cost on target points will bring many challenges to plan the trajectories of UAVs. Therefore, guaranteeing the fairness of energy consumption with motion, communication and hovering energy consumption in consideration is important and challenging for multi-UAV reconnaissance system.

In this paper, we investigate how UAVs should optimally exploit their mobility via trajectory planning to achieve the fairness of energy consumption with communication, hovering and motion energy consumption in consideration. Obviously, this problem aims to minimize the maximum energy consumption among the reconnaissance UAVs. First, we formulate this optimization problem as a min-max tour cover problem which has been proved to be NP-hard. And then, we propose a heuristic algorithm to minimize the maximum energy consumption of reconnaissance UAVs by planning the trajectories. However, the heuristic algorithm has no rigorous theoretical analysis and cannot provide performance guarantees. Therefore, we propose an approximation algorithm which can be used under scenarios with strict and firm energy requirements. The main contributions of this paper are summarized as follows:

- To the best of our knowledge, this is the first time to study the fairness of energy consumption of multi-UAV in reconnaissance scenario with communication, hovering and motion energy consumption in consideration. We formulate it as a min-max tour cover problem which has been proved to be NP-hard.
- To resolve the fairness issue, we propose a heuristic algorithm to minimize the maximum energy consumption of reconnaissance UAVs. Firstly, the ant colony algorithm is used to obtain a tour. Secondly, the tour splitting algorithm is adopted to get the trajectory of each UAV.
- To provide performance guarantees and rigorous theoretical analysis, we propose an efficient approximation algorithm to optimize the trajectories to achieve the fairness of energy consumption under scenarios with strict energy requirements. The approximation algorithm uses the Christofides algorithm to calculate a tour. And then we propose a novel splitting algorithm to split it. We prove that the approximation ratio of the proposed algorithm is 2.5.
- Extensive simulations are conducted under different settings to evaluate the performance of our proposed algorithms. The results show that the maximum energy

consumption of reconnaissance UAVs can be reduced by 71.6% and 74.2% at most by approximation algorithm and heuristic algorithm, respectively. Meanwhile, the standard deviation of the proposed algorithms is lower than compared algorithms, which further verifies the fairness of energy consumption among all the UAVs.

The rest of this paper is organized as follows. In Section II, we briefly survey related works. Section III presents the system model and problem formulation. Section IV introduces the heuristic algorithm. In Section V, we propose an approximation algorithm. Section VI shows the approximation ratio analysis and proof. Section VII presents extensive simulation results for performance evaluation. Conclusions follow in Section VIII.

II. RELATED WORK

A. ENERGY CONSUMPTION

As UAVs are energy-constrained due to the limited on-board battery, it is paramount to save the energy to prolong the multi-UAV system's lifetime in reconnaissance applications. Most of works focused on reducing total energy consumption, while only a few of works considered the fairness of energy consumption problem. In [11], Wu *et al.* proposed a novel class of energy-efficient wireless robot reconnaissance system, where both the positions and transmit powers of the mobile relay and sensing robots may be optimized in order to minimize the total communication-motion energy consumption. In [12], the optimal 3D trajectory of each UAV was obtained in a way that the total energy used for the mobility of the UAVs was minimized while serving the ground Internet of Things devices. In [13], an UAV's energy consumption was modeled as a function of flight speed and operation conditions such as climbing, hovering, and so on. They aimed to find the optimal speed that minimized the total energy consumption. Kim *et al.* [14] considered the k traveling salespersons with neighborhood problem, which aimed to find k closed moving trajectories for the k mobile collectors such that the total length of the trajectories was minimized. An UAV trajectory optimization problem with detailed propulsion energy consumption considering both velocity and acceleration was studied in [15]. The authors studied UAV-enabled wireless communication, where rotary-wing UAV is dispatched to send/collect data to/from multiple ground nodes (GNs) [16]. They aimed to minimize the total UAV energy consumption, including both propulsion energy and communication-related energy, while satisfying the communication throughput requirement of each GN. It can be seen that, although the above works discussed the energy consumption in different wireless networks, the fairness of energy consumption problem of multi-UAV in reconnaissance applications still needs to be further studied.

B. MIN-MAX TOUR COVER PROBLEM

In a metric graph, the UAV trajectory planning problem is equivalent to covering all vertices in the graph with k tours such that the maximum tour weight is minimized. We refer to this as the min-max tour cover problem. Many previous works investigated the min-max tour cover problem. In [17], the authors aimed to find routes for the vehicles to collectively visit all the customers such that the maximum traveling cost of the vehicles was minimum. Xu *et al.* [18] studied a min-max location-routing problem, which aimed to determine both the home depots and the tours for a set of vehicles to service all the customers in a given weighted graph, so that the maximum working time of the vehicles was minimized. In [19], Xu *et al.* designed approximation algorithms and derived inapproximability results for min-max path cover problems. Zhao *et al.* [20] designed trajectories of multiple mobile collectors such that the maximum data gathering time among the mobile collectors was minimized. Xu *et al.* [21] focused on devising approximation algorithms that achieved constant approximation ratios for the min-max tour cover problem and its variants. Sathyan *et al.* [22] designed a cluster-first approach which did not take the vertices weight into consideration. To sum up, most of works did not consider the point's cost. In the reconnaissance mission, it represents the communication and hovering energy consumption. Therefore, these works cannot be directly applied to solve the fairness of reconnaissance UAV energy consumption.

C. APPROXIMATION ALGORITHM OF MIN-MAX TOUR COVER PROBLEM

Some related literatures studied the min-max tour cover problem, where their feasible solutions were a set of tours. In [23], Prasad *et al.* studied the min-max tree cover problem related to the min-max tour cover problem. For one thing, the optimal value of the min-max tree cover problem cannot be greater than that of the min-max tour cover problem. For another thing, by duplicating each edge of a feasible solution of min-max tree cover problem, we obtain a feasible solution of min-max tour cover problem with a doubled objective value. Even *et al.* [23] and Arkin *et al.* [24] provided a 4-approximation algorithm for min-max tree cover problem. Xu *et al.* [18] also derived a 6-approximation algorithm. Xu *et al.* improved the approximation ratio to $\frac{16}{3}$ [21]. Prasad *et al.* [25] gave a three phase algorithm to solve task allocation and presented 5-approximation algorithm. Khani and Salavatipour [26] presented a 2.5-approximation algorithm for min-max tree cover problem and improved the 3-approximation bound. There were other literatures studying the min-max tour cover problem without the use of min-max tree cover problem. Frederickson *et al.* proposed a $(1 + e - 1/k)$-approximation algorithm where e is the best approximation ratio for the classic TSP problem [27]. For the uncapacitated rooted min-max tour cover problem, Xu *et al.* [21] developed a $6\frac{1}{3}$-approximation algorithm.

III. SYSTEM MODEL AND PROBLEM FORMULATION

A. NETWORK MODEL

As shown in Fig. 1(b), we consider a reconnaissance scenario where UAVs are employed to serve $n > 1$ target points whose

TABLE 1. Main notations used in the paper.

Notation	Definition
v_j	Target point j
U_i	Reconnaissance UAV i
n	Number of target points
k	Number of trajectories, or number of reconnaissance UAVs
E_{tx}	Communication energy consumption
E_{hv}	Hovering energy consumption
E_m	Motion energy consumption
E_{U_i}	Total energy consumption of U_i
$v_{\max}$	Maximum velocity
H	Altitude of UAVs
t_{hv}^j	Hovering time over v_j
N_j	Amount of data over v_j
B	Information transmission rate
α	Path loss exponent
d	Transmission distance
S_R	Initial location
$g_{U_i}^{v_j}$	Binary coverage variable
$S_i(t)$	Position of the U_i at time t
$l_i(t)$	U_i trajectory projected on the ground
$\dot{l}_i(t)$	Time derivative of $l_i(t)$
$d_{\min}$	Minimum inter-UAV distance
UT_i	Trajectory of reconnaissance UAV U_i

distribution follows a homogeneous Poisson Point Process (PPP). In this paper, we only consider one relay UAV [11]. Under this scenario, the distance between the target area and the base station is too long to ensure that the UAVs with limited energy complete the whole mission. Hence, reconnaissance UAVs collect the information from the target area, and they only need to transmit it to the relay UAV instead of the base station. Then the relay UAV delivers the information to base station. In this paper, the energy consumption of a reconnaissance UAV mainly consists of two parts. The first part is the communication-related energy consumption for circuitry and signal processing. The other part is the propulsion energy consumption, which is required for the UAV to remain hovering and move freely [16], [28]–[31]. In fact, we mainly aim to propose an algorithm, which is applicable for any energy consumption model. The extension to more realistic energy consumption models will be left for our future work.

The multi-UAV system is modeled as a complete undirected graph $G = (V, E)$, where each vertex in V represents a target point to be covered and each edge in E represents a path to be travelled. For vertex $v_j \in V$, a vertex weight $h(v_j)$ is given to represent the communication and hovering energy consumption. For edge $e(v_j, v_{j+1}) \in E$, an edge weight $w(v_j, v_{j+1})$ represents the motion energy consumption. The optimization objective is to cover all vertices in the graph with k tours such that the maximum tour weight which includes the vertices weight and edges weight is minimized. To tackle this problem, we formulate it as a min-max tour cover problem.

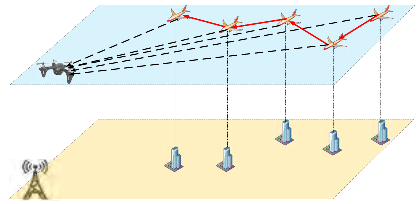


FIGURE 2. Position-critical communication model.

It is an extension of the well-known Traveling Salesman Problem (TSP). The TSP is NP-hard when $k = 1$, the min-max tour cover problem is also NP-hard for any $k \geq 1$ [21].

B. PROPULSION ENERGY CONSUMPTION MODEL

The propulsion energy consumption is required for the UAV to remain aloft and move freely [16]. In our paper, the UAVs fly at a constant height. Under this condition, the major propulsion energy consumption includes motion and hovering energy consumption. The motion energy consumption mainly depends on the trajectory length of UAV movement. Therefore, the motion energy consumption E_m can be expressed as [31]–[33]

$$E_m = Q \cdot l, \tag{1}$$

where Q is the energy consumption rate per unit length, measured in J/m, and l represents the trajectory length that the UAV has to move.

Under many scenarios, such as taking picture and shooting video, reconnaissance UAVs have to hover for a period of time t_{hv}^j for collecting information over target point v_j. The hovering energy consumption of reconnaissance UAVs per unit time is defined as P_{hv}. The hovering energy consumption can be modeled as [32]

$$E_{hv}^j = t_{hv}^j \cdot P_{hv}. \tag{2}$$

The hovering time t_{hv}^j can be calculated based on the amount of data N_j that needs to be transmitted at each point v_j. Furthermore, the information transmission rate is defined as B. Therefore, the hovering energy consumption is given by

$$E_{hv}^j = \frac{N_j}{B} \cdot P_{hv}. \tag{3}$$

C. COMMUNICATION ENERGY CONSUMPTION MODEL

In this paper, the communication energy consumption model is based on what is defined in [31]. The energy required for successful wireless data transmission is affected by the distance between two communication nodes and other factors like noises, interferences, and multi-path fading.

As shown in Fig. 2, we use the position-critical communication model [33]. In this model, a reconnaissance UAV needs to collect information from target points, and immediately transmits the information to the relay UAV. The communication energy consumed over target point v_j to transmit N_j bits over distance d can be expressed as

$$E_{tx}^j = N_j \cdot d^{\alpha} \cdot e_{tx}, \tag{4}$$

where e_{tx} is the energy to transmit one bit over one meter and α is the path loss exponent of the transmission medium, which depends on the transmission environment. In addition, d is the distance between the reconnaissance UAV and the relay UAV.

D. PROBLEM FORMULATION

According to [15] and [16], we assume that UAVs fly horizontally at a constant altitude H. All UAVs start from an initial location $S_R = (x_R, y_R, H)$ to execute reconnaissance mission. We assume that one of the UAVs is used as a static relay UAV, which located at S_R, and the remaining k UAVs are used as reconnaissance UAVs. Meanwhile, the number of reconnaissance UAVs is less than the number of the target points.

In order to complete the whole reconnaissance mission, each reconnaissance UAV is responsible for different target points. We introduce the following binary coverage variable $g_{U_i}^{v_j} \in \{0, 1\}$, for $\forall v_j \in$ target points, $U_i \in$ reconnaissance UAVs such that

$$g_{U_i}^{v_j} = \begin{cases} 1 & U_i \textit{ covers target point } v_j \\ 0 & \textit{otherwise}. \end{cases} \tag{5}$$

Without loss of generality, we consider a three-dimensional (3D) Cartesian coordinate system where the coordinate of target point v_j is located at $(x_j, y_j, 0)$. The time-varying coordinate of reconnaissance UAV U_i can be expressed as $S_i(t) = (x_i^t, y_i^t, H)$, with x_i^t and y_i^t denoting the reconnaissance UAV's time-varying x-coordinate and y-coordinate, respectively. And we denote UAV U_i trajectory projected on the ground as $l_i(t) \in \mathbb{R}^{2\times 1}$. The distance from reconnaissance UAV U_i to the relay UAV can be expressed as

$$d_{S_i(t),R} = \sqrt{(x_i^t - x_R)^2 + (y_i^t - y_R)^2}. \tag{6}$$

The communication energy consumption of reconnaissance UAV U_i can be expressed as

$$E_{tx}^i = \sum_{v_j \in UT_i} N_j \cdot d_{v_j,R}{}^{\alpha} \cdot e_{tx}, \tag{7}$$

where UT_i is the trajectory of reconnaissance UAV U_i.

The total energy consumption of reconnaissance UAV U_i includes communication, motion and hovering energy consumption,

$$E_{U_i} = E_{tx}^i + E_m^i + E_{hv}^i. \tag{8}$$

Thus, the total energy consumption of reconnaissance UAV U_i can be obtained as

$$E_{U_i} = \sum_{v_j \in UT_i} N_j \cdot d_{v_j,R}{}^{\alpha} \cdot e_{tx} + \sum_{l \in UT_i} Q \cdot l + \sum_{v_j \in UT_i} \frac{N_j}{B} \cdot P_{hv}, \tag{9}$$

Assuming that the locations of target points are known, the objective is to minimize the maximum total energy consumption of the reconnaissance UAVs by optimizing their trajectories. Define $E_{\max} = \max_{1\le i\le k} E_{U_i}$ as the function of $S_i(t)$. The optimization problem is formulated as

$$\min_{S_i(t)} E_{\max} \tag{10}$$

$$s.t. \left\| \dot{l}_i(t) \right\| \le v_{\max}, \quad \forall i, t, \tag{11}$$

$$\|l_i(t) - l_{i'}(t)\| \ge d_{\min}, \quad \forall i \ne i', t \tag{12}$$

$$\sum_{1\le i\le k} g_{U_i}^{v_j} = 1, \quad \forall v_j. \tag{13}$$

In (10), $S_i(t)$ is the optimization variable, which represents the position of the reconnaissance UAV U_i in time t. In practice, the trajectories of UAVs are also subject to the maximum velocity $v_{\max}$ constraint (11), where $\dot{l}_i(t)$ denotes the time derivative of $l_i(t)$. As UAVs fly at the same altitude, the trajectories of UAVs are also subject to the collision avoidance constraint [34]. In (12), $d_{\min}$ denotes the minimum inter-UAV distance to ensure collision avoidance. The constraint (13) ensures that each target point v_j is covered by exactly one reconnaissance UAV.

IV. HEURISTIC ALGORITHM

We put forward a heuristic algorithm to plan the trajectory of each reconnaissance UAV. The main idea of this algorithm is to get a trajectory covering all target points, and then decompose the trajectory. This algorithm is mainly divided into three steps. First of all, we utilize the ant colony algorithm to calculate a trajectory. As a new class of global searching algorithms, it could solve TSP problems [35]. Then, the trajectory is decomposed into k segments by using tour splitting algorithm [19]. At last, since each reconnaissance UAV needs to go back to the initial location, we join S_R to plan the k closed trajectories [36].

The tour splitting for heuristic algorithm to obtain k segments is summarized in Algorithm 1 and proceeds as follows. First of all, we define B_i as the bound vector, *i.e.* $B_i = \frac{i}{k} \cdot W(C)$, where $W(C) = w(C) + h(C)$. In this algorithm, $w(C)$ and $h(C)$ represent the weight of all edges and the weight of all vertices in tour C, respectively (Line 1). Next, in order to take the weight of vertices into consideration in the decomposition process, we define $wh(v_j, v_{j+1})$ as a new weight variable (Line 2). And then, for each segment C_i, we find the ending point $v_{j(i)}$ such that the segment $(v_0, \ldots, v_{j(i)})$ satisfies $wh(v_o, v_1, \ldots, v_{j(i)}) \le B_i$ (Line 3). After finding $v_{j(i)}$, we can obtain k segments $C = \{C_1, \ldots, C_i, \ldots, C_k\}$ for reconnaissance UAVs (Line 4-5).

V. APPROXIMATION ALGORITHM

Although it is simple, the heuristic algorithm has no rigorous theoretical analysis and cannot provide performance guarantees. In this section, we propose an approximation algorithm for the fair energy consumption problem. It can be applied to certain scenarios where the Quality of Service (QoS) performance is critical. As shown in Fig. 3, the approximation algorithm mainly includes three steps. First of all, the Christofides

Algorithm 1 Tour Splitting for Heuristic Algorithm

Input: $G = (V, E)$, tour C, k.
Output: k segments of tour C.

Compute $B = (B_1, \ldots, B_i, \ldots, B_k)$, $B_i = \frac{i}{k} W(C)$;
Denote $wh(v_j, v_{j+1}) = w(v_j, v_{j+1}) + h(v_j) + h(v_{j+1})$;
$v_{j(i)} \leftarrow \left\{wh(v_o, v_1, \ldots, v_{j(i)}) \leq B_i\right\} \wedge (v_{j(i)} \in V)$;
Starting vertex of next segment $v'_{j(i)} = v_{j(i)+1}$;
Get the segment $C_i = (v'_{j(i-1)}, \ldots, v_{j(i)})$, for $1 \leq i \leq k$.

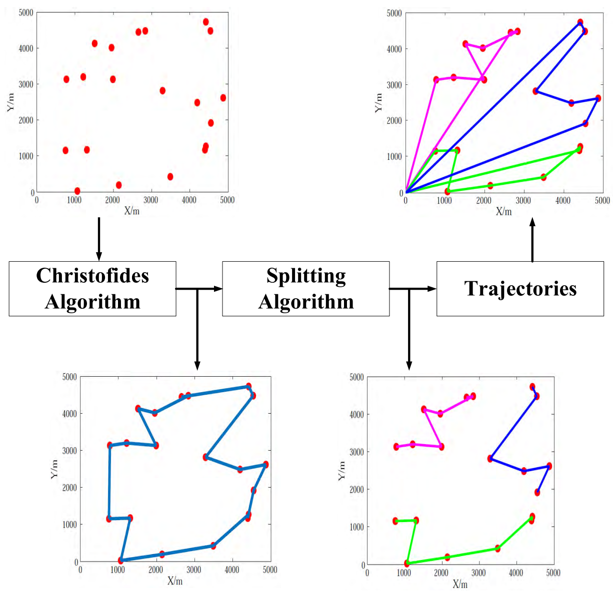


FIGURE 3. **Approximation algorithm.**

Algorithm 2 Christofides Algorithm

Input: $G = (V, E)$, $w(v_j, v_{j+1})$, $\forall v_j, v_{j+1} \in V$.
Output: tour C

1: $MST \leftarrow (\forall v_j \in V, v_j \in MST) \wedge w(MST) = \min$;
2: $D \leftarrow (v_j \in V) \wedge (\mathrm{mod}(\deg ree(v_j), 2) == 1)$;
3: $M \leftarrow (v_j \in D) \wedge w(M) = \min$;
4: $H \leftarrow (e(v_j, v_{j+1}) \in M) \vee (e(v_j, v_{j+1}) \in MST)$;
5: $EC \leftarrow (e(v_j, v_{j+1}) \in H) \wedge (times(e(v_j, v_{j+1})) = 1)$;
6: $C = EC - repeat\ vertices$.

Algorithm 3 Tour splitting for approximation algorithm

Input: $G = (V, E)$, tour C, k.
Output: k segments of tour C.

Compute $B = (B_1, \ldots, B_i, \ldots, B_k)$, $B_i = \frac{i}{k} W(C)$;
Construct $VE = (ve_0 = v_0, ve_1 = e(v_0, v_1), ve_2 = v_1, ve_3 = e(v_1, v_2), \ldots, ve_{2n+1} = v_0)$;
Denote $wh\{ve_0, ve_1\} = h(v_0) + w(v_0, v_1)$;
$ve_{j(i)} \leftarrow \{wh(ve_o, ve_1, \ldots, ve_{j(i)}) \leq B_i\} \wedge \{(ve_{j(i)} \in E) \vee (ve_{j(i)} \in V)\}$;
if $ve_{j(i)} \in E$ **then**
  $ve_{j(i)} = ve_{j(i)-1}$, $ve'_{j(i)} = ve_{j(i)+1}$;
else
  $ve_{j(i)} = ve_{j(i)-2}$, $ve'_{j(i)} = ve_{j(i)}$;
end if
Get the segments $C = \{C_1, \ldots, C_i, \ldots, C_k\}$, $C_i = (ve'_{j(i-1)}, \ldots, ve_{j(i)})$, for $1 \leq i \leq k$.

algorithm is used to calculate a tour C covering all target points. And then, a novel tour splitting algorithm is proposed to split tour C into k segments. This tour splitting algorithm can achieve better fairness than the approach proposed in [19]. Finally, for k segments, we join the initial location S_R to construct k closed trajectories of reconnaissance UAVs. Trajectory UT_i contains the path to be travelled and the target points to be covered.

A. CHRISTOFIDES ALGORITHM

The Christofides algorithm is improved by the double spanning tree algorithm, so the worst solution is within 1.5 times of the optimal solution, and the worst solution of the double spanning tree algorithm is within 2 times of the optimal solution [37]. As of 2017, this is the best approximation ratio that has been proved for the TSP on general metric spaces, although better approximations are known for some special cases. In our approximation algorithm, we use the Christofides algorithm as shown in Algorithm 2 to calculate a tour C covering all target points.

We model the multi-UAV system as a complete undirected graph $G = (V, E)$, where each vertex in V represents a target point to be covered and each edge in E represents a path to be travelled. The Christofides algorithm proceeds as follows. First of all, we compute a minimum spanning tree MST which covers all vertices (Line 1). A minimum spanning tree or minimum weight spanning tree is a subset of the edges of a connected, edge-weighted (un)directed graph that connects all the vertices together, without any cycles and with the minimum possible total edge weight. In the MST, we build a set D to store target points with odd degrees (Line 2). Node degree is the number of edges associated with the node. According to the handshaking lemma, D has an even number of vertices. The target points in D constitute a subgraph, and we find a minimum-weight perfect matching M (Line 3). This step is a key step in this algorithm and a difference from the double spanning tree algorithm which repeats all the edges to obtain the cycle. We combine the edges of M and MST to form a connected multi-graph H in which each vertex has even degree (Line 4). In multi-graph H, we form an Eulerian circuit EC which covers all target points (Line 5). Some points are more than once covered in the EC. Therefore, we make the EC found in previous step into a Hamiltonian circuit by skipping repeated vertices (Line 6).

B. SPLITTING ALGORITHM

In order to guarantee the fairness of energy consumption, we propose a novel tour splitting algorithm as shown in Algorithm 3 to get the trajectory of each reconnaissance UAV.

At the beginning of algorithm, we compute the bound vector $B = (B_1, \ldots, B_i, \ldots, B_k)$ which is the key to divide tour C into k segments (Line 1). B_i is calculated based on the total weight of the vertices and edges of tour C, $B_i = \frac{i}{k} \cdot W(C)$, where $W(C) = w(C) + h(C)$, for all $1 \leq i \leq k$. $w(C)$ and $h(C)$ represent the weight of all edges and the weight of all vertices in tour C, respectively. B_i represents the weight of demarcation point between the segments in the tour C. Second, along the path we construct a sequence of vertices and edges which contains $2n + 1$ elements, and denote it as $VE = (ve_0 = v_0, ve_1 = e(v_0, v_1), ve_2 = v_1, ve_3 = e(v_1, v_2), \ldots, ve_{2n+1} = v_0)$, $e(v_j, v_{j+1})$ represents edge between two points (Line 2). The sequence consists of vertices and edges in tour C in order. The weight of vertices and edges is defined as $wh(ve_0, \ldots, ve_j)$ (Line 3). The weight of each vertex is only calculated once, which is different from [19]. In this way, the weight of vertices is taken into account in the tour splitting. Then, we find k demarcation points that satisfy the fairness conditions (Line 4). From the first element ve_0, for each i, $1 \leq i \leq k$, we find an ending vertex $ve_{j_{(i)}}$ along the tour C such that the weight of the segment $wh(ve_o, ve_1, \ldots, ve_{j(i)})$ satisfies $wh(ve_o, ve_1, \ldots, ve_{j(i)}) \leq B_i$. There may be two cases at the demarcation point (Line 5-9).

Case 1: If demarcation point $ve_{j(i)}$ is an edge, we would delete this edge when we build the tour. We define the ending vertex of this segment as $ve_{j(i)} = ve_{j(i)-1}$, and the starting point of the next segment is defined as $ve'_{j(i)} = ve_{j(i)+1}$ (Line 5-6).

Case 2: If demarcation point $ve_{j(i)}$ is a vertex, we would take this point as the starting point for the next segment. We define the ending vertex of this segment as $ve_{j(i)} = ve_{j(i)-2}$ (Line 7-9).

Finally, we obtain a set of $C = \{C_1, \ldots, C_i, \ldots, C_k\}$ which represents k segments of the tour C. Segment C_i contains the edges to be travelled and the vertices to be covered (Line 10).

VI. ALGORITHM ANALYSIS

In this section, we prove the approximation ratio of the proposed approximation algorithm and analyze its time complexity.

Before analyzing trajectory UT_i, we analyze the properties of segments obtained by Algorithm 3.

Lemma 1: For Algorithm 3, segment C_i that it returns satisfies:

$$\begin{aligned} cost(C) &= \max_{1\leq i\leq k} \{w(C_i) + h(C_i)\} \\ &\leq B_i - B_{i-1} + \max_{v_j\in V} \ h(v_j) \\ &= \frac{W(C)}{k} + \max_{v_j\in V} h(v_j), \end{aligned} \tag{14}$$

where $cost(C)$ represents the maximum energy consumption of k segments and $w(C_i)$ is the total weight of all edges of segment C_i. The total weight of all vertices of segment C_i is defined as $h(C_i)$. In addition, we define the maximum vertex weight as $\max_{v_j\in V} \ h(v_j)$.

Proof: According to the first step to the fourth step in Algorithm 3, there are four cases for $ve_{j(i-1)}$ and $ve_{j(i)}$, where $ve_{j(i-1)}$ satisfies $wh(ve_0, \ldots, ve_{j(i-1)}) \leq B_{i-1}$ and $ve_{j(i)}$ satisfies $wh(ve_o, ve_1, \ldots, ve_{j(i-1)}, \ldots, ve_{j(i)}) \leq B_i$.

Case 1: The demarcation point $ve_{j(i-1)}$ and $ve_{j(i)}$ are edges. According to the fifth and sixth step in Algorithm 3, the starting point of segment C_i is defined as $ve'_{j(i-1)} = ve_{j(i-1)+1}$. Meanwhile, the ending point of segment C_i is defined as $ve_{j(i)} = ve_{j(i)-1}$. Therefore we can obtain

$$w(C_i) + h(C_i) \leq B_i - B_{i-1}. \tag{15}$$

Case 2: The demarcation point $ve_{j(i-1)}$ and $ve_{j(i)}$ are vertices. According to the seventh and eighth step in Algorithm 3, the starting point of segment C_i is defined as $ve'_{j(i-1)} = ve_{j(i-1)}$. Meanwhile, the ending point of segment C_i is defined as $ve_{j(i)} = ve_{j(i)-2}$. Therefore we can obtain

$$w(C_i) + h(C_i) \leq B_i - B_{i-1} + \max_{v_j\in V} h(v_j). \tag{16}$$

Case 3: The demarcation point $ve_{j(i-1)}$ is an edge and $ve_{j(i)}$ is a vertex. According to the fifth and sixth step in Algorithm 3, the starting point of segment C_i is defined as $ve'_{j(i-1)} = ve_{j(i-1)+1}$. According to the seventh and eighth step in Algorithm 3, the ending point of segment C_i is defined as $ve_{j(i)} = ve_{j(i)-2}$. Therefore we can obtain

$$w(C_i) + h(C_i) \leq B_i - B_{i-1}. \tag{17}$$

Case 4: The demarcation point $ve_{j(i-1)}$ is a vertex and $ve_{j(i)}$ is an edge. According to the seventh and eighth step in Algorithm 3, the starting point of segment C_i is defined as $ve'_{j(i-1)} = ve_{j(i-1)}$. According to the fifth and sixth step in Algorithm 3, the ending point of segment C_i is defined as $ve_{j(i)} = ve_{j(i)-1}$. Therefore we can obtain

$$w(C_i) + h(C_i) \leq B_i - B_{i-1} + \max_{v_j\in V} h(v_j). \tag{18}$$

In conclusion, for segment $C_i = (ve'_{j(i-1)}, \ldots, ve_{j(i)})$, we can obtain

$$w(C_i) + h(C_i) \leq B_i - B_{i-1} + \max_{v_j\in V} h(v_j), \quad \forall i. \tag{19}$$

We define the weight of the segment with the maximum weight as $cost(C) = \max_{1\leq i\leq k} \{w(C_i) + h(C_i)\}$. For this, for $1 \leq i \leq k$, Eq. 14 can be obtained directly. ■

For k segments, we join the initial location S_R to construct k closed trajectories of reconnaissance UAVs. Next, we analyze the properties of trajectory UT_i.

Lemma 2: According to Lemma 6.1, trajectory set UT satisfies:

$$\begin{aligned} cost(UT) &= \max_{1\leq i\leq k} \{w(UT_i) + h(UT_i)\} \\ &\leq \frac{W(C)}{k} + \max_{v_j\in V} \ h(v_j) + 2 \max_{v_m\in V} w(S_R, v_m), \end{aligned} \tag{20}$$

where $cost(UT)$ represents the maximum energy consumption of k trajectories.

TABLE 2. Relationship between the optimized problem and the graph theory representation.

Graph theory representation	Optimized problem
$\cos t(UT)$	Objective function $E_{\max}$
UT_i	Optimization variable $S_i(t)$
$w(UT_i)$	Motion energy consumption E_m
$h(UT_i)$	Communication and hovering energy consumption $E_{tx} + E_{hv}$
opt	Optimal maximum energy consumption of reconnaissance UAVs
C_i	Trajectory of UAV excluding starting point
$h(v_j)$	Communication and hovering energy consumption on target point v_j
$w(v_j, v_{j+1})$	Motion energy consumption flying between v_j and v_{j+1}
$\max\limits_{v_j \in V} h(v_j)$	Maximum communication and hovering energy consumption on target point
$\max\limits_{v_m \in V} w(S_R, v_m)$	Maximum motion energy consumption from starting point to target point

Proof: For a set of k segments $C = \{C_1, \ldots, C_i, \ldots, C_k\}$, we join the initial location S_R to form k closed trajectories UT. The total energy consumption of a closed trajectory needs to add two parts of motion energy consumption, from S_R to the segment and from the segment back to the S_R. The energy consumption of these two parts is $w(S_R, ve'_{j(i-1)}) + w(ve_{j(i)}, S_R)$. It satisfies $w(S_R, ve'_{j(i-1)}) + w(ve_{j(i)}, S_R) \leq 2 \max\limits_{v_m \in V} w(S_R, v_m)$. We can obtain

$$cost(UT) = cost(C) + w(S_R, ve'_{j(i-1)}) + w(ve_{j(i)}, S_R) \leq \frac{W(C)}{k} + \max_{v_j \in V} h(v_j) + 2 \max_{v_m \in V} w(S_R, v_m). \tag{21}$$

■

To analyze the approximation ratio of proposed approximation algorithm, we prove the following lower bound opt of this min-max tour cover problem.

Lemma 3: For the min-max tour cover problem in this paper, we can obtain

$$opt \geq \max\{\frac{w(C^*)+h(C)}{k}, 2 \max_{v_m \in V} w(S_R, v_m) + \max_{v_j \in V} h(v_j)\}, \tag{22}$$

where C^* is the optimal tour for covering all vertices in V, opt is the optimal maximum energy consumption of reconnaissance UAVs.

Proof: For the optimal solution P^* to the min-max tour cover problem, since $\cup_{i=1}^{k} P_i^*$ covers all vertices of V and adds edges which are from S_R to the segment and edges which are from the segment back to S_R, we have $\sum\limits_{i=1}^{k} w(P_i^*) \geq w(C^*)$, which implies $\sum\limits_{i=1}^{k} \{w(P_i^*) + h(P_i^*)\} \geq w(C^*) + h(C)$. Therefore, there must exist $P_i^* \in P^*$ with $w(P_i^*) + h(P_i^*) \geq \frac{w(C^*)+h(C)}{k}$. Thus, $opt \geq \frac{w(C^*)+h(C)}{k}$.

Reconnaissance UAVs start from the initial location S_R to cover the target area. $w(S_R, v_m)$ is proportional to the distance from the target point to the relay UAV. Amount of data

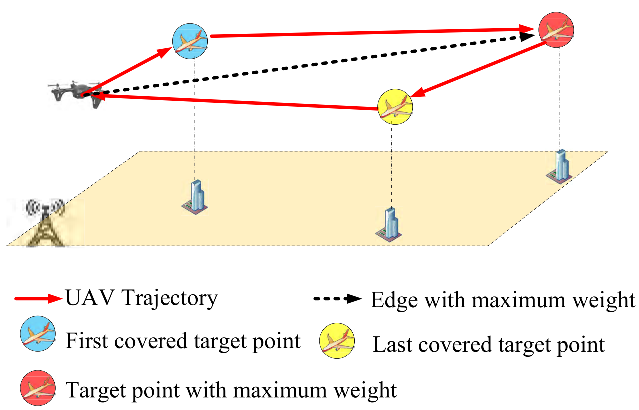


FIGURE 4. The second possible scenario.

collected by the reconnaissance UAVs at each target point is comparable, which means the hovering energy consumption is roughly the same. Meanwhile, the point farthest from the relay UAV is also the target point where the communication energy consumption is the maximum. Therefore, we can obtain $\max\limits_{v_m \in V} w(S_R, v_m)$, $\max\limits_{v_j \in V} h(v_j)$, $m = j$.

We prove $opt \geq 2 \max\limits_{v_m \in V} w(S_R, v_m) + \max\limits_{v_j \in V} h(v_j)$ from the following three possible scenarios.

Case 1: The most energy-consuming UAV covers the target point with the maximum vertex weight, and this target point is the first point to be covered. Therefore, opt includes $\max\limits_{v_m \in V} w(S_R, v_m)$ and $\max\limits_{v_j \in V} h(v_j)$. In this case, inequality $opt \geq 2 \max\limits_{v_m \in V} w(S_R, v_m) + \max\limits_{v_j \in V} h(v_j)$ must be satisfied.

Case 2: The most energy-consuming UAV covers the target point with the maximum vertex weight, and this target point is not the first point to be covered. As shown in Fig. 4, red solid lines represent the trajectory of the reconnaissance UAV, and black dotted line represents $\max\limits_{v_m \in V} w(S_R, v_m)$. According to the triangle inequality, $opt \geq 2 \max\limits_{v_m \in V} w(S_R, v_m) + \max\limits_{v_j \in V} h(v_j)$.

Case 3: The most energy-consuming UAV does not cover the target point with the maximum vertex weight. In this case, its energy consumption is definitely greater than that of the

UAV which covers $\max_{v_j \in V} h(v_j)$. Moreover, the above two cases have proved that the inequality is true when the UAV covers the target point with the maximum vertex weight. ■

From Lemma 6.3, we can obtain the following theorem, which implies that the approximation algorithm can achieve 2.5-approximation ratio.

Theorem 4: Approximation algorithm proposed in previous section can achieve an approximation ratio of 2.5 for the min-max tour cover problem.

Proof: By Lemma 6.2, we obtain $cost(UT) \leq \frac{W(C)}{k} + \max_{v_j \in V} h(v_j) + 2 \max_{v_m \in V} w(S_R, v_m)$. This implies that for $i = 1, \ldots, k$, the total weight of each trajectory $UT_i \in UT$, must satisfy $w(UT_i) + h(UT_i) \leq \frac{W(C)}{k} + \max_{v_j \in V} h(v_j) + 2 \max_{v_m \in V} w(S_R, v_m)$.

We use the Christofides algorithm to calculate tour C. It is an approximation algorithm that guarantees its solutions will be within a factor of $\frac{3}{2}$ of the optimal solution length [37]. Therefore, we can obtain $w(C) \leq \frac{3}{2} w(C^*)$. Thus,

$$\begin{aligned} W(C) &= w(C) + h(C) \\ &\leq \frac{3}{2} w(C^*) + h(C) \\ &\leq \frac{3}{2} \left\{ w(C^*) + h(C) \right\}, \end{aligned} \tag{23}$$

and

$$\frac{W(C)}{k} \leq \frac{3}{2} \cdot \frac{\{w(C^*) + h(C)\}}{k}. \tag{24}$$

Moreover, by Lemma 6.2 and Lemma 6.3, we have

$$\begin{aligned} cost(UT) &\leq \frac{W(C)}{k} + \max_{v_j \in V} h(v_j) + 2 \max_{v_m \in V} w(S_R, v_m) \\ &\leq \frac{3}{2} \cdot \frac{\{w(C^*) + h(C)\}}{k} \\ &\quad + \max_{v_j \in V} h(v_j) + 2 \max_{v_m \in V} w(S_R, v_m) \\ &\leq \frac{3}{2} opt + opt \\ &\leq \frac{5}{2} opt. \end{aligned} \tag{25}$$

Hence, the proposed approximation algorithm can achieve an approximation ratio of 2.5. ■

Theorem 5: Given a metric complete graph $G = (V, E)$ and a positive integer k, there is a 2.5-approximation algorithm for the fair energy consumption problem, which takes $O(n^3)$ time.

Proof: The approximation algorithm includes three steps, mainly two algorithms, Christofides algorithm and tour splitting algorithm. First, we analyze the time complexity of the Christofides algorithm. This algorithm consists of two parts: the calculation of a minimum spanning tree and finding a minimum-weight perfect matching. Finding the *MST* in G takes $O(n^2)$ time. The time complexity of minimum-weight perfect matching algorithm is $O(n^3)$. Therefore, the time complexity of Christofides algorithm is $O(n^3)$ [37]. Second, we analyze the time complexity of the tour splitting algorithm. The time complexity of the tour splitting algorithm is related to the number of target points. The tour splitting algorithm takes $O(n)$ time. The overall time complexity of 2.5-approximation algorithm is $O(n^3)$. ■

TABLE 3. Simulation parameters.

Definition	Parameters	Values
Target area size	D	$5km \times 5km$
Altitude of UAVs	H	$50m$
Maximum velocity	$v_{\max}$	$20m/s$
Movement parameter	Q	$13.19J/m$
Information transmission rate	B	$2Mbps$
Hovering energy parameter	P_{hv}	$237J/s$
Amount of data	N_j	$20Mb$
Path loss exponent	α	2
Communication energy parameter	e_{tx}	$10pJ/(m \cdot bit)$
Minimum inter-UAV distance	$d_{\min}$	$100m$

VII. SIMULATION RESULTS

In this section, simulation results are provided to evaluate the performance of our proposed heuristic algorithm (HA) and approximation algorithm (AA).

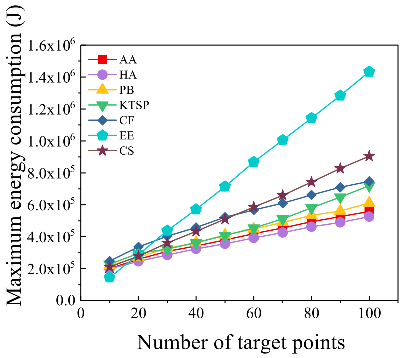
A. SIMULATION SETUP

For our simulations, we assume that n target points are distributed in a square area of side length equal to $5km$. All UAVs start from an initial location $(0, 0, H)$. Moreover, it is assumed that UAVs fly at a fixed altitude of 50m, and the minimum inter-UAV distance is set to $100m$ [34]. We set the maximum velocity to be $20m/s$. According to the energy consumption models in Section III, we assume the movement parameter Q equals to $13.19J/m$ and the hovering energy parameter P_{hv} equals to $237J/s$. We set communication energy parameter e_{tx} to be $10pJ/(m \cdot bit)$ [38]. As stated in [39], the simple free space propagation model can be utilized for estimating the link performance for air-to-air links. Therefore, we set the path loss exponent to be 2. The simulation parameters are listed in Table 3.

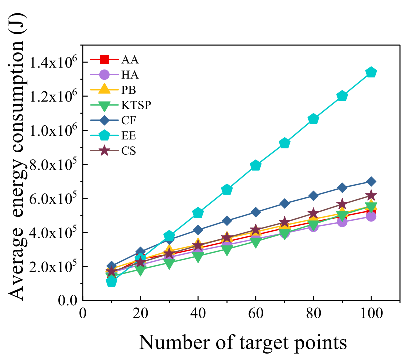
B. SIMULATION RESULTS

In this subsection, we conduct extensive simulations under different settings. We present simulation results to validate the performance of our proposed algorithms as compared to the following five benchmark schemes:

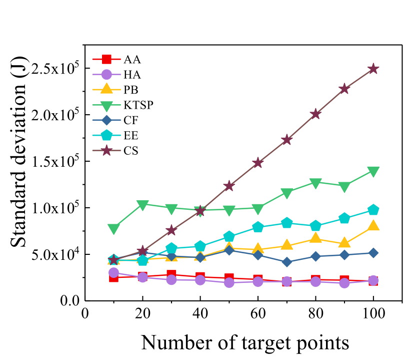
- PB algorithm: each UAV is responsible for the same number of target points. It calculates a trajectory to cover all target points and then decomposes the trajectory.
- KTSP algorithm: it utilizes the K-Traveling Salesman Problem (KTSP) algorithm to get the trajectory of each reconnaissance UAV [40].
- CF algorithm: it first assigns n target points into k clusters and then uses the TSP algorithm to calculate the trajectory for each cluster [22].



(a) Maximum energy consumption



(b) Average energy consumption



(c) Standard deviation

FIGURE 5. Different number of target points.

- EE algorithm: it uses the Hungarian method to solve the assignment problem. And then it finds the optimal trajectories of the UAVs [12].
- CS algorithm: it proposes a trajectory planning method based on Cuckoo Search (CS) algorithm [41].

1) DIFFERENT NUMBER OF TARGET POINTS

We set the number of reconnaissance UAVs to be 3 and compare the seven algorithms under different number of target points. Fig. 5(a) shows the trend of the maximum energy consumption of the seven algorithms. The maximum energy consumption of heuristic algorithm is reduced by $5.6\% - 63.3\%$ compared with other five algorithms. The maximum energy consumption of approximation algorithm is reduced by $4.5\% - 61\%$ compared with other five algorithms. As the number of target points increases, the advantages of our algorithms are more obvious. This is mainly because the increase of target points leads to add communication and hovering energy consumption. Meanwhile, our algorithms consider the point's cost which represents the communication and hovering energy consumption. However, the other five algorithms only calculate the edges weight as the total weight when planning the trajectory. As shown in Fig. 5(a), we can also observe that the maximum energy consumption of EE algorithm is larger than other algorithms when $m \geq 30$. This is due to the fact that EE algorithm is mainly applicable to time-varying ground networks. However, in this paper, the target points' locations are fixed during the whole mission. In addition, it only considers the minimization of total energy consumption.

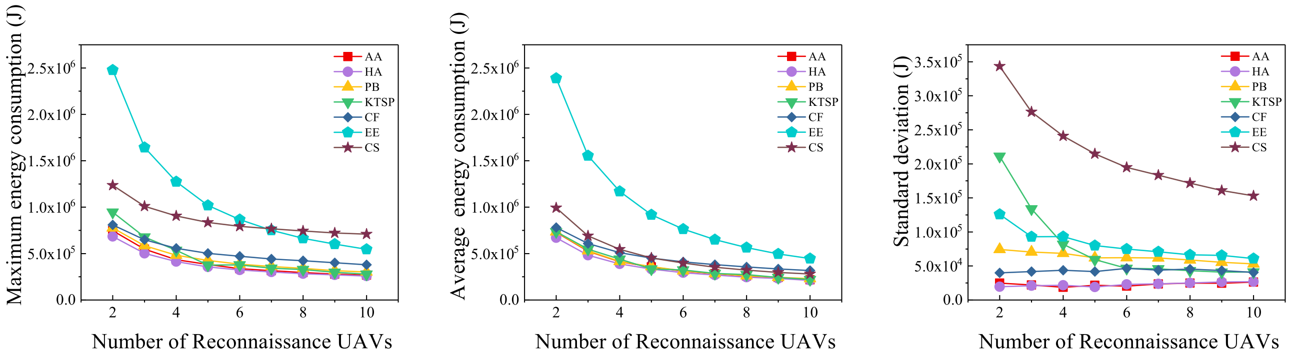
Fig. 5(b) shows the trend of average energy consumption as the number of target points changes. When the number of points is less than 70, the average energy consumption of KTSP algorithm is lower than our proposed algorithms. However, when the number of points is greater than 70, the average energy consumption of our algorithms is the lowest. This is mainly because the proportion of point's weight increases as the number of target points increases. From Fig. 5(c) we can see the standard deviation of seven algorithms. Compared with other five algorithms, the standard deviation of heuristic algorithm is reduced by $29.7\% - 91.6\%$ and the standard deviation of approximation algorithm is reduced by $39.2\% - 91.5\%$. The standard deviation of CS algorithm is very large. This is reasonable since it only considers minimizing the total energy consumption, while neglecting the individual UAV energy consumption. CS algorithm is a feasible scheme, but it cannot guarantee the performance. The performance of PB algorithm is the closest to the approximation algorithm because different tour splitting algorithms are used in the same tour. However, from Fig. 5(c), the results show that the fairness of our tour splitting algorithm is better than PB algorithm.

2) DIFFERENT NUMBER OF RECONNAISSANCE UAVS

Second, we set the number of target points to be 100 and compare the seven algorithms under different number of reconnaissance UAVs. Fig. 6(a) and Fig. 6(b) show that the maximum energy consumption and the average energy consumption decrease as the number of reconnaissance UAVs increases. In fact, increasing the number of reconnaissance UAVs is not an effective approach since it also increases the cost. When the number of UAVs is above 5, the average energy consumption and the maximum energy consumption drop very slowly and they also bring economic pressure. Therefore, when the number of reconnaissance UAVs is greater than 5, the advantages of our algorithms are not obvious. Fig. 6(c) shows that as the number of UAVs increases, the standard deviation of our algorithms is minimal.

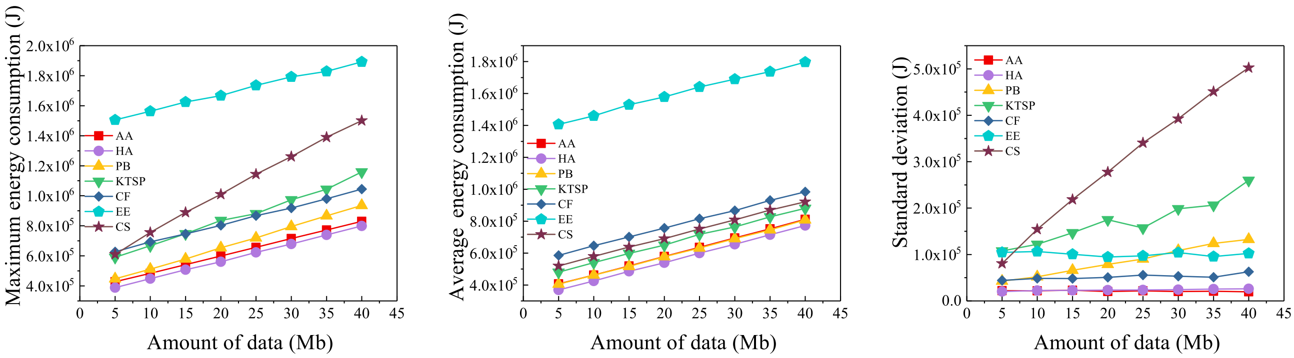
3) DIFFERENT AMOUNT OF DATA

We set the number of target points to be 120, the number of reconnaissance UAVs to be 3 and compare the seven algorithms under different amount of data. Fig. 7(a) shows that the maximum energy consumption increases as the amount of data increases. The maximum energy consumption of heuristic algorithm is reduced by $12.2\% - 74.2\%$ compared with other five algorithms. The maximum energy consumption of approximation algorithm is reduced by $4.3\% - 71.6\%$ compared with other five algorithms. As the amount of data



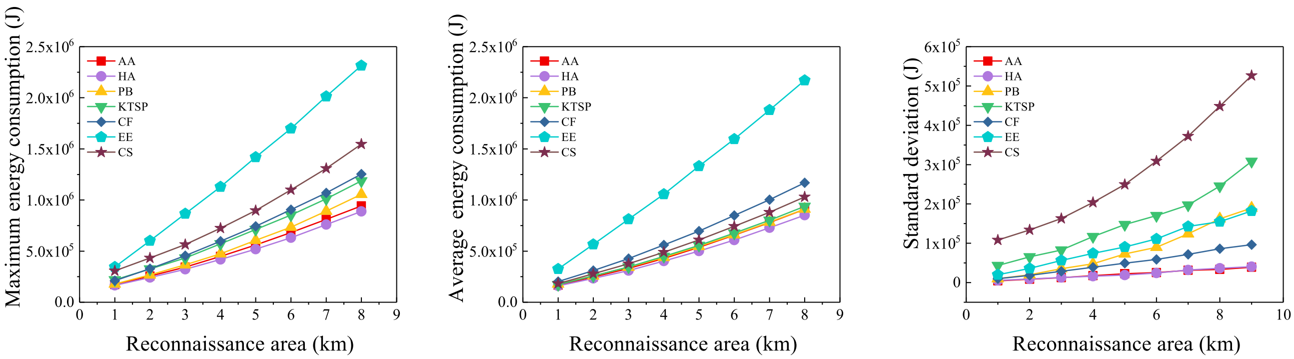
(a) Maximum energy consumption (b) Average energy consumption (c) Standard deviation

FIGURE 6. **Different number of reconnaissance UAVs.**



(a) Maximum energy consumption (b) Average energy consumption (c) Standard deviation

FIGURE 7. **Different amount of data.**



(a) Maximum energy consumption (b) Average energy consumption (c) Standard deviation

FIGURE 8. **Different reconnaissance area sizes.**

increases, the proportion of communication and hovering energy consumption in total energy consumption increases. Therefore, the advantages of our proposed algorithms are more obvious. By combining Fig. 7(a) and Fig. 7(b), it is found that EE algorithm is a feasible scheme which is suitable for dynamic networks, but it has the worst performance in static networks. Fig. 7(b) shows that the performance of PB algorithm is the closest to our algorithms. However, its standard deviation is much larger than our algorithms as shown in Fig. 7(c). On the contrary, the standard deviation of CF algorithm is the closest to our algorithms, but the maximum and average energy consumption are large.

4) DIFFERENT RECONNAISSANCE AREA SIZES

We set the number of target points to be 100, the number of reconnaissance UAVs to be 3 and compare the seven algorithms under different reconnaissance area sizes. The reconnaissance area we considered is square, and the abscissa

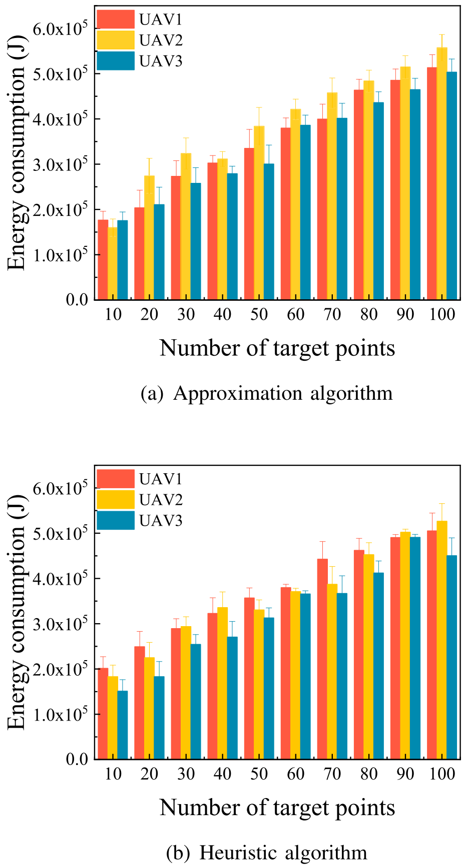


FIGURE 9. Energy consumption of each reconnaissance UAV.

of Fig. 8 represents the side length of reconnaissance area. As the reconnaissance area becomes larger, the flying range of UAVs becomes larger, resulting in more motion energy consumption. Therefore, the maximum energy consumption and average energy consumption increase as the scope of the reconnaissance area increases. As shown in Fig. 8, the proposed algorithms perform the best under different reconnaissance area sizes. When the reconnaissance area size increases, heuristic algorithm exhibits better performance than approximation algorithm. Compared with other five algorithms, the maximum energy consumption of heuristic algorithm is reduced by $7\% - 63.4\%$ and the maximum energy consumption of approximation algorithm is reduced by $3.1\% - 60.5\%$. By observing Fig. 8(b) and Fig. 8(c), it is found that the average energy consumption and standard deviation of our proposed algorithms are also the lowest under different reconnaissance area sizes.

5) ENERGY CONSUMPTION OF EACH RECONNAISSANCE UAV

Fig. 9 shows the trend of energy consumption of each reconnaissance UAV as the number of target points changes. As can be seen from the figure, the proposed two algorithms can guarantee the fairness of energy consumption between reconnaissance UAVs, because the energy gap between three UAVs is small.

VIII. CONCLUSION

This paper has studied the fair-energy trajectory plan problem for multi-UAV system in reconnaissance mission. The maximum energy consumption is minimized by planning the trajectory of each reconnaissance UAV. We first convert the formulated optimization problem into a min-max tour cover problem. Then we propose a heuristic algorithm and an approximation algorithm whose approximation ratio is 2.5. Finally, numerical results are provided to evaluate the performance of the proposed algorithms under different setups. The results show our algorithms can reduce the maximum energy consumption of reconnaissance UAVs by 74.2% at most, as compared with other five algorithms. In addition, there are many other interesting research directions that could be pursued in our future work. For one thing, we will consider other practical constraints on UAV trajectory, such as the maximum turning angle and maximum acceleration. For another thing, we will consider planning the relay UAV's trajectory.

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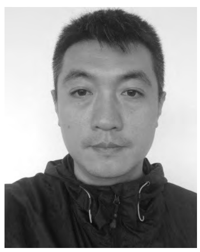

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