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Fair-Energy Trajectory Planning for Multi-Target Positioning Based on Cooperative Unmanned Aerial Vehicles

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ABSTRACT Owing to the flexibility and low cost, cooperative Unmanned Aerial Vehicles(UAVs) have been attractive in multi-target positioning recently. Although it is popular and easy to accomplish, positioning based on trilateration method still faces challenges under scenarios with multiple UAVs. First, large accumulated errors will be brought if a single UAV is used to perform trilateration on same targets. Second, due to the mobility of targets, the time interval between UAVs performing twice successive distance measurement on one target cannot be long for positioning precision. Finally, the limited energy provided by onboard battery limits the time for UAVs to perform tasks. Once the energy used by some of the UAVs reaches limitation, the whole positioning mission will fail. Thus, to complete the mission of locating multiple targets, this paper is intended to minimize the maximum energy consumption among all UAVs. We formulate the problem, and decompose it into two subproblems, one of which plans the routes for UAV groups and the other plans the routes for UAVs in a group. To solve the first subproblem, a heuristic algorithm called adjusted genetic algorithm (AGA) is proposed to plan trajectories for all UAV groups under constraints on maximum energy consumption. To guarantee stable performance and reduce computation complexity, we propose an approximation algorithm, Tree Decomposition united with Christofides Algorithm (TDCA), and the approximation ratio is proved to be $(3 * N'/(2 * (N' - 1)))$, where N' denotes the number of UAV groups. For the second subproblem, a two-step greedy heuristic algorithm is proposed to plan trajectories for UAVs in same groups. Extensive simulations show that compared to existing algorithms, the proposed algorithms can reduce up to 26.6% maximum and 26.3% average energy consumption.

INDEX TERMS Trajectory planning, energy consumption, cooperative UAVs, approximation algorithm, tree decomposition, Christofides algorithm.

I. INTRODUCTION

Over past few decades, industry and academia have paid much attention to Unmanned Aerial Vehicles (UAVs) because of their advantages in flexible mobility and low cost. As shown in Fig. 1, among all aspects of applications, multi-target positioning performed by multiple UAVs has been used most extensively, *e.g.*, military reconnaissance [1], [2] and target detection [3]. UAVs have better performance in multi-target positioning mission for the reasons listed below. First, sending people to perform positioning mission is difficult and dangerous in scenarios such as depopulated zone or radiation zone, *etc*. Second, since the quality of aerial-to-ground channel is better than ground-to-ground channel [4], [5], positioning by UAVs will bring about high precision compared with positioning by Unmanned Ground Vehicles (UGVs) [6]. Recently, with the miniaturization of UAVs, it becomes a tendency to execute mission cooperatively. Cooperative work by multiple UAVs is more flexible and robust than that by a single UAV. Therefore, it is worthwhile studying cooperative multiple UAVs performing multi-target positioning.

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FIGURE 1. Locating targets by UAVs.

Different UAVs locating different targets is a most straightforward idea for multiple UAVs to perform multi-target positioning. Zhang *et al.* [7] used the method of single-site positioning with received signal strength indicator (RSSI) to locate single target once at a time. There are several kinds of position information needed to complete single-site positioning, *e.g.*, azimuth angle, pitch angle and the distance between UAV and target. Besides, it is also necessary to get accurate position coordinates and attitude angles of UAV itself. Therefore, single-site positioning by single UAV requires relatively complex measurement means and more position information which would lead to accumulated errors. To simplify measurement methods and take the advantage of cooperative work of multiple UAVs, trilateration [8] method requiring only three times of distance measurement is adopted in this paper.

In theory, three times of distance measurement needed for trilateration are supposed to be carried out by one single UAV or several different UAVs. However, the onboard equipment will bring accumulated inherent errors in scenario where only one UAV is used to perform trilateration. Hence, three different UAVs are used to implement three times of distance measurement. Furthermore, we need to overcome two challenges in trilateration. One is that there need to be a bound on the time interval between twice successive distance measurement because of targets' ability to move and mission requirement (quick attack on mobile targets). The other is that the onboard energy for UAV is finite and once some UAVs' energy consumptions reach limitation, the positioning mission will fail because of their quit. Thus, it is vital to study the problem of how to achieve fair energy consumption among UAVs.

UAVs track the signals of the targets to locate them in many current works [10]- [14]. Authors in [10], [11] tracked targets by using single UAV flying towards them. Instead of flying towards targets, a few sensors or UAVs adopted angle of arrival (AOA) and RSSI methods to locate targets in [12], [14]. Dai *et al.* [12] used static sensors to locate static targets. Meanwhile, Sallouha *et al.* [14] used aerial anchors to locate one target at a time, ignoring the superiority of cooperative work in saving time in multi-target positioning mission. To save time consumed in multi-target positioning mission, planning the trajectories for cooperative UAVs is extremely necessary. The problem of planning trajectories for multi-UAV in multi-target scenario can be regarded as a Multiple Travelling Salesman Problem (MTSP) if multiple UAVs are viewed as salesmen while multiple targets have different positions. There have already existed some works planning the trajectory for UAVs by solving MTSP problem [18]–[22]. However, in this paper three different UAVs are needed when locating one target base on trilateration method, which makes the problem of trajectory planning for cooperative multiple UAVs performing multi-target positioning different from traditional MTSP problem.

In this paper, we intend to minimize the maximum energy consumption among all UAVs to balance the energy consumption by planning trajectories. Apparently, the mission is to locate multiple targets with cooperative UAVs with trilateration method under the objective of minimizing the maximum energy consumption. This min-max problem is decomposed into two subproblems, a multiple travelling salesmen problem and an allocation problem. For the first subproblem, a heuristic algorithm and an approximation algorithm are proposed to help solve it. Then, a two-step greedy algorithm is proposed for the second subproblem. To sum up, the contributions are listed below:

- We study the problem with the intention to minimize the maximum energy consumption among all UAVs, which performs cooperative multi-target positioning with trilateration method, which is much simpler than single-site positioning. The problem is decomposed into two subproblems, an MTSP problem followed by an allocation problem.
- We propose a heuristic algorithm, an adjusted genetic algorithm, to help solve the MTSP problem. The heuristic algorithm can provide better performance with the increase of iteration times. To guarantee stable performance and reduce computation complexity, we propose an approximation algorithm, Tree Decomposition Algorithm united with Christofides Algorithm (TDCA).
- We propose a greedy heuristic algorithm to help solve the allocation problem. After solving the MTSP problem, a two-step greedy algorithm is proposed to allocate the three coarse-grained positions around targets to three UAVs in one group.
- We perform extensive simulations to verify the effectiveness of the two proposed algorithms. Compared to three other algorithms, simulation results show that the proposed TDCA combined with two-step greedy algorithm can reduce up to 26.6% of maximum energy consumption while the two-stage heuristic algorithm can reduce up to 24.9% maximum energy consumption.

The rest of this paper is organized as follows. In Section II, related works are reviewed. Section III builds the models and Section IV formulates and decomposes the problem. Section V proposes a heuristic as well as an approximation algorithms for Subproblem 1 and Section VI proposes a heuristic algorithm for Subproblem 2. Section VII shows the simulation results and discusses the performance of algorithms. Section VIII is the conclusion for this paper.

II. RELATED WORKS

In this section, current works on UAV based multi-target positioning is reviewed first, and then we review works about UAVs' trajectory planning based on MTSP.

A. UAV BASED MULTI-TARGET POSITIONING

To complete the task of positioning, some works use UAVs equipped with RSSI sensors to track the targets. Assuming the transmission power of target to be unknown, authors in [9]–[11] tracked the target with different estimation methods. Based on the theory of Differential Received Signal Strength Indication (DRSSI), Dehghan *et al.* [9] compared three different estimation filters to track single target without considering the scenario of multiple targets. Authors in [10] and [11] tracked the targets using extended Kalman Filter (EKF) with different states of targets, *i.e.*, static and dynamic. However, they all ignored the energy consumption of the UAVs and can track only one target at a time.

Some works use both RSSI and AOA sensors to locate targets. Dai *et al.* [12] proposed a numerical method to improve the accuracy of distance measurement with three sensors in different positions with the transmit power known. But the sensors above are static and cannot move around in a multi-target scenario. Then, Haidari *et al.* [13] proposed a method by using a network established of several static sensors and a guided moving sensor to locate multiple RF sources with unknown transmit power. Sallouha *et al.* [14] used three aerial anchors strictly arranged in equilateral triangle to locate the targets. Since they did not take the energy consumption of UAVs into consideration either, methods they proposed cannot be used to solve the problem this paper proposed.

B. MTSP BASED COOPERATIVE TRAJECTORY PLANNING

For cooperative trajectory planning, there have been many works planning path by solving multiple travelling salesman problem (MTSP) [15]- [22].

The authors in [15] and [16] both used GA to solve the problem of path planning with UAVs acting as relay nodes in message ferry networks and collecting information from desired regions respectively. Chen *et al.* [17] are dedicated to solving the multi-robot patrolling problem under the consideration of two objectives, minimizing both the maximum and the total tour distances. To solve multi-objective MTSP, Shim *et al.* [18] hybridized local search metaheuristic approaches with the decomposition estimation of distribution algorithm to enhance the search behavior of the algorithm. Considering the existing environmental and inherent instability, Sariel-Talay *et al.* [19] solved multiple traveling robots problem with a multi-robot cooperation framework employing a dynamic task selection scheme.

Existing works also proposed algorithms to solve MTSP by transforming the problem into TSPs. Gu *et al.* [20] transformed the original problem, a variant of MTSPs into a standard asymmetric TSP and solved it with Lin-Kernighan Heuristic searching algorithm. The objective is to avoid static obstacles/threats detected and subjecting to aircraft dynamical constraints. Kim *et al.* [21] considered two multiple-drone-assisted search-and-reconnaissance scenarios, defined the problems as variations of TSP and utilized graph theory to solve them. Authors in [22] solved TSP problem with two heuristic algorithms, improved genetic algorithm and particle-swarm-optimization-based ant colony optimization (ACO) algorithm, but the results of these two algorithms depend on their iteration times. In conclusion, existing works have done a lot of research on MTSP by directly solving it or transforming it into TSPs. However, the proposed algorithms achieved better results with the decrease of time complexity. Furthermore, because of the trilateration method used in this paper, there would be a new problem that the trajectory of three UAVs need to be planned respectively. Thus, existing works cannot solve the problem of planning the trajectory for UAVs when using trilateration to locate targets.

TABLE 1. Notations.

Notations	Definitions
N	number of UAVs
M	number of targets
n	UAV n, $n \in \{1, 2, ...N\}$
m	target m, $m \in \{1, 2, ...M\}$
U_n	location of UAV n
H_0	altitude of UAV
$T(m)$	location of target m
$P_r(d)$	signal strength received at the distance d
$q(n, k)$	location of the UAV n performing the kth positioning
$d^n_{mo}(k)$	distance of the UAV n flying through in kth positioning
E^n_{mo}	motion energy consumption of the UAV n
E^n_{com}	communication energy consumption of the UAV n
E^n_p	positioning energy consumption of the UAV n
E^n_{total}	total energy consumption of the UAV n
K_n	positioning times of UAV n
δ_t	maximum time interval
e_η	energy consumption limitation for one UAV

III. MODELS

In this section, we build models including network model, distance measurement model, positioning model and energy consumption model, to prepare for the problem formulation. The major notations used are listed in Table 1.

A. NETWORK MODEL

We establish a system including a central station, N UAVs and M targets illustrated in Fig.2. The calculations on the information sent from UAVs will be executed by the central station to get target position. For each target, it is supposed that the three surrounding positions have already been known to UAVs so that they can perform trilateration on targets. This assumption is usual in real scenario, *e.g.*, delivering sensors to surveillance area by aerial vehicles. Since the application is to detect sensor network in wild scene where high obstacles are barely existing, the UAVs are assumed to fly straightly without considering obstacles. The precise positions of these sensors are unknown because the delivery is affected by many factors, such as wind power, air friction and terrain. Fortunately, three or more coarse-grained positions which surround

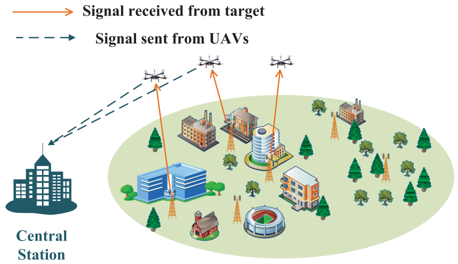


FIGURE 2. UAVs locate the targets based on RSSI and send the position information to the central station.

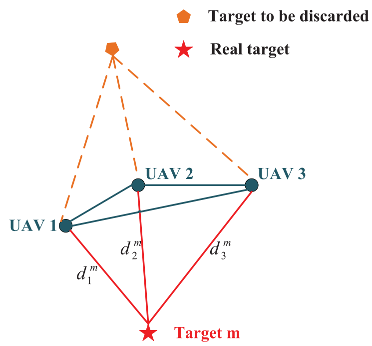


FIGURE 3. There are two solutions to the equations of the trilateration method. One of them can be discarded based on height information.

the deliver position can be achieved and trilateration can be implemented by UAVs in these positions. At the same time, it is assumed that the sensor targets will send out messages by transmitting wireless signals with transmit power already known. Under this assumption, we can locate these sensor targets with trilateration method based on RSSI. To implement positioning mission, we need to confine the distance between the target and the UAV to the transmission range. We also limit the time interval between twice continuous distance measurement to a limitation. Furthermore, owing to the fact that one UAV conducting trilateration may bring about accumulated inherent hardware errors, we are supposed to ensure that one target will be located by three different UAVs.

For simplicity, we settle the N collaborative UAVs in the central station with the coordinate of $[0, 0, 0]^T$ initially and then denote the location of UAV in flight by $U_n = [x_n, y_n, z_n]^T (n \in \{1, 2, \ldots, N\})$. All UAVs will fly at the same height which is denoted by H_0. When locating targets, the UAVs will send out messages to the central station, including both their own position information and detection information, the distance measurement information and the positioning time. In addition, the received information and the coordinate of the target m, $T(m) = [x(m), y(m), z(m)]^T$, $m \in \{1, 2, \ldots, M\}$ will be analyzed and calculated by the central station.

B. DISTANCE MEASUREMENT MODEL

Since we have already known the transmit power of the target and equipped all the UAVs with onboard RSSI devices, the classic log-distance path loss model is adopted to measure distances between UAVs and targets [10]- [14]. During the propagation of the wireless signal, the received signal strength is attenuated as the distance increases. According to this law, the relationship between the RSSI attenuation and the distance can be obtained. There existed several channel fading models, *e.g.*, Rayleigh fading model and free space fading model. In this paper since the model is only used for distance measurement and does not influence trajectory planning, we choose free space fading model as follows for ease of presentation:

$$P_r(d) = P_0 - 10\lambda \lg(d/d_0), \tag{1}$$

where d_0 represents the reference distance and the signal strength at distance d_0 is denoted by P_0. The real distance and the signal strength received at real distance are denoted by d and P_r, respectively. The path loss exponent is represented by λ.

C. POSITIONING MODEL

Fig. 3 reveals the schematic diagram of positioning model based on trilateration method performed on targets by UAVs.

We denote the positions of the three UAVs by $(x_1, y_1, z_1)^T$, $(x_2, y_2, z_2)^T$, $(x_3, y_3, z_3)^T$ respectively. Distances between the mth target and the three UAVs are represented as d_1^m, d_2^m, d_3^m. Let the coordinate of the target be $(x(m), y(m), z(m))^T$, and then we formulate the equation of trilateration as

$$\begin{cases} (d_1^m)^2 = (x(m) - x_1)^2 + (y(m) - y_1)^2 + (z(m) - z_1)^2 \\ (d_2^m)^2 = (x(m) - x_2)^2 + (y(m) - y_2)^2 + (z(m) - z_2)^2 \\ (d_3^m)^2 = (x(m) - x_3)^2 + (y(m) - y_3)^2 + (z(m) - z_3)^2. \end{cases} \tag{2}$$

After solving equation (2), we will obtain two positions for target and discard one of them based of UAV flying height. To sum up, the target can be precisely located after completing the three times of distance measurement between UAVs and target.

D. ENERGY CONSUMPTION MODEL

The energy consumed by UAV can be divided into three parts: energy for motion, energy for positioning and energy for communication.

The energy for motion ensures that the UAV can move and keep aloft. In this paper, UAVs are supposed to fly in constant speed and since the power does not vary too much in low speed condition, the time for UAV to fly is corresponding to the length of flying routes when performing tasks. Thus, we calculate the energy consumption based on UAV flying routes. Project the trajectory of the nth UAV on the horizontal plane, and denote it by $q(n, t) = [x(n, t), y(n, t)]^T$. For ease of presentation, UAV's trajectory is assumed to be discretized into K_n segments, representing K_n times positioning. The distance from the position for the nth UAV to perform the $(k-1)$-th positioning to the position to perform the k-th positioning can be written as $d_{mo}^{n}(k) = ||q(n,k) - q(n,k-1)||$. The energy for motion is

$$E_{mo}^{n}(k) = e_{mo} \cdot d_{mo}^{n}(k) = e_{mo} \left\| q(n,k) - q(n,k-1) \right\|, \tag{3}$$

where the energy consumed per unit horizontal distance is denoted by e_{mo} and measured in *Joule/meter* [23].

The energy for positioning is related to the time that UAV uses to hover and to range. Observe that the difference between the energy consumed per second for flying and hovering is minor. The time used to hover for UAVs to perform distance measurement is very short, since we only need to get the strength of the signal in this position, which can be done in no more than one second. Thus, the assumption is made that the positioning-related energy can be simplified into a constant $E_p^n(k) = e_p$ corresponding to the energy for UAV to fly for one second [24]. Moreover, the energy consumed by distance measurement is much smaller than the energy for motion. We then express the energy consumed by the nth UAV to perform the kth positioning as

$$E_{sum}^{n}(k) = E_{mo}^{n}(k) + E_{com}^{n}(k) + E_{p}^{n}(k) = e_{mo}||q(n,k) - q(n,k-1)|| + e_p. \tag{4}$$

The energy for communication $E_{com}^{n}(k)$, is much smaller than the energy consumed to ensure UAV's motion in practice according to [26]. Therefore, we will ignore it when considering the total energy consumption in this paper. Then, the total energy consumed by nth UAV is expressed as

$$E(n) = \sum_{k=1}^{K_n} E_{sum}^{n}(n,k) = \sum_{k=1}^{K_n} [e_{mo}||q(n,k) - q(n,k-1)|| + e_p]. \tag{5}$$

IV. PROBLEM FORMULATION AND DECOMPOSITION

In this section, the trajectory planning problem is formulated with the intention to minimize the maximum energy consumption. To solve this min-max problem, the UAVs will be divided into groups with three UAVs each so that the problem can be decomposed into two subproblems.

A. PROBLEM FORMULATION

We formulate the optimization problem to minimize the maximum energy consumed by all UAVs below.

$$\min_{q,m} \max_{n=1}^{N} \sum_{k=1}^{K_n} \left[e_{mo} \cdot \|q(n,k) - q(n,k-1)\| + e_p \right] \tag{6}$$

$$s.t.\ d_{m_i} = ||U_n - T(m)||, m_i \neq m_j, i \neq j, \quad and \quad i,j = 1,2,3, \tag{C6-1}$$

$$d_{m_i} \leq R, \tag{C6-2}$$

$$t_m(i) - t_m(i-1) \leq \delta_t, \tag{C6-3}$$

$$\sum_{k=1}^{K_n} [e_{mo} \cdot ||q(n,k) - q(n,k-1)|| + e_p] \leq e_\eta. \tag{C6-4}$$

We explain the constraints above in detail in the below. To avoid twice distance measurement on one target being continuously performed by the same UAV, we record the positioning information as $d_{m_i} = \|U_n - T(m)\|$ with m_i marking the UAV performing the ith distance measurement on the mth target and satisfying the constraint that the mth target should be located by three different UAVs as illustrated in (C6-1). In (C6-2), R represents the upper bound of the maximum distance between UAV and target. Inequation (C6-3) expresses that the time interval between the twice successive distance measurement, ith and $(i-1)$th, on the same target should be as small as possible, where the time of the ith distance measurement on the mth target is denoted by $t_m(i)$ and δ_t is supposed to be as small as possible so that the time intervals among UAVs locating the same target can also be small correspondingly. Then, the target can be located within a relatively small time interval with relatively high precision considering their possibility of moving. Since the onboard battery carried by the UAV provides limited energy, we should constrain the energy consumed to implement the mission to an upper bound denoted by e_η in (C6-4).

B. DECOMPOSITION

For ease of presentation, the problem formulated can be viewed as to allocate multiple targets to multiple UAVs to locate, which is more like an MTSP problem. The difference is that UAVs acting as travelling salesmen in our problem has to cover three positions surrounding the targets instead of directly locating targets themselves. Thus, our formulated problem is more intractable than a pure MTSP problem and is difficult to be directly solved.

In this subsection,we propose to decompose it into two subproblems. The basic idea is dividing UAVs into groups of three. These UAV groups will be treated as travelling salesmen. According to the theory of trilateration, three coarse-grained positions around the target need to be covered by UAVs. Thus, each group will have three UAVs and the centroid of the three known positions will be viewed as a city. We first need to plan routes for these travelling salesmen to cover all the cities, which can be treated as an MTSP problem. Then, each group will be recovered as three UAVs and each city will be recovered as three positions. The second subproblem is to allocate UAVs to cover all the locations so that we can get exact routes for all UAVs.

After the UAVs being divided into groups of three, each group of three UAVs will be treated as a unit, which covers the same set of targets in the same order, in which case constraints (C6-1) and (C6-3) can be omitted. In this paper, N UAVs are supposed to be divided into $N' = N/3$ groups. If N is less than 3 or N is not divisible by 3, the remaining UAVs which cannot form a group will result in accumulated error when performing three times of distance measurement on the same target. Besides, if we use more than 3 UAVs to locate one target, because we assume that each distance measurement is accurate without error, only three

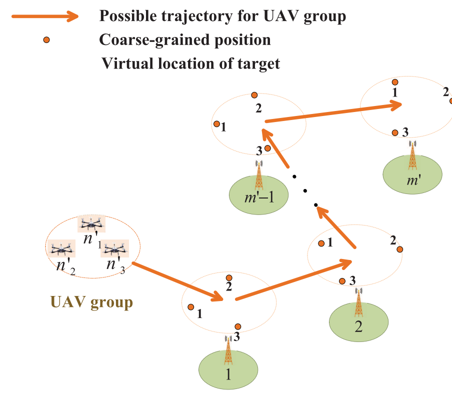


FIGURE 4. A possible trajectory of a UAV group. A UAV group contains three UAVs. The centroid of three known positions of a target is considered as the virtual location of the target. The trajectory passes through the virtual locations of multiple targets.

times of distance measurement will be used and this will result in resource waste. Thus, N is supposed to be a multiply of 3 and then the optimization problem will be reformulated as

$$\min_{m} \max_{n'=1}^{N/3} \sum_{k=1}^{K_{n'}} \left[e_{mo} \cdot \left\| q(n', k) - q(n', k-1) \right\| + e_p\right] \tag{7}$$

$$s.t. \quad d_{m_i} = ||U(n', k) - T(m)|| \leq R, \tag{C7-1}$$

$$\sum_{k=1}^{K_{n'}} [e_{mo} \cdot ||q(n', k) - q(n', k-1)|| + e_p] \leq e_\eta. \tag{C7-2}$$

The n'th UAV group will cover $K_{n'}$ targets. The problem formulated intends to minimize the maximum energy consumption among all UAV groups. The problem seems to have similarity to the MTSP problem with each group corresponding to a salesman and the centroid of the three positions surrounding the target to a city.

The two subproblems are defined in the below.

- Subproblem 1: Plan routes for the salesmen to cover all cities and minimize the maximum cost among all salesmen.
- Subproblem 2: Allocate the three positions recovered from each city to the three UAVs recovered from each salesman and minimize the maximum energy of the energies consumed by the three UAVs.

1) SUBPROBLEM 1: MTSP PROBLEM WITH MIN-MAX OBJECTIVE

Fig. 4 illustrates the Subproblem 1 planning the trajectories for all UAV groups, which has similarity to an MTSP problem [15]. Nevertheless, the objective of the traditional MTSP problem is to minimize the total cost of all salesmen. Subproblem 1 has a major difference from the traditional MTSP problem is that its objective is to minimize the maximum energy consumed by all UAV groups, which corresponds to minimize the maximum cost. We formulate the problem below:

$$\min \max_{n'=1}^{N/3} \sum_{k=1}^{K_{n'}} \left[e_{mo} \cdot \left\| q(n', k) - q(n', k-1) \right\| + e_p\right] \tag{8}$$

$$s.t. \sum_{k=1}^{K_{n'}} [e_{mo} \cdot ||q(n', k) - q(n', k-1)|| + e_p] \leq e_\eta, \tag{C8-1}$$

$$q(n', 1) = q(n', K_{n'}). \tag{C8-2}$$

The objective is to minimize the maximum energy consumption among all UAV groups under constraints on energy consumption in (C8-1). And once the UAV consumed e_η energy or the whole positioning mission is finished, this UAV group has to quit the mission and return to the central station, as illustrated in (C8-2).

2) SUBPROBLEM 2: PLANNING ROUTES FOR UAVS IN EACH GROUP

Each UAV group will be recovered as three UAVs and each city will be recovered as three positions in Subproblem 2. Then, allocating the three positions to the three UAVs will be considered.

Take one UAV group as an example. There assume to be M' targets which will be covered by this UAV group. We let $p(m', i)$ denote one of the three coarse-grained positions around the m'th target which is allocated to the ith UAV, in which case the ith UAV will pass through $p(m', i)$.

We formulate Subproblem 2 as

$$\min_{p} \max_{i=1}^{3} \sum_{m'=1}^{M'} \left[e_{mo} \cdot \left\| p\left(m', i\right) - p\left(m'-1, i\right) \right\| + e_p\right] \tag{9}$$

$$s.t.\ p\left(m', i\right) \neq p\left(m', j\right),\ i, j \in \{1, 2, 3\},\quad i \neq j \tag{C9-1}$$

$$\sum_{m'=1}^{M'} \left[e_{mo} \cdot \left\| p\left(m', i\right) - p\left(m'-1, i\right) \right\| + e_p\right] \leq e_\eta, \quad \forall i \in \{1, 2, 3\} \tag{C9-2}$$

$$p(0, i) = p\left(m'+1, i\right), \quad \forall i \in \{1, 2, 3\} \tag{C9-3}$$

The objective is to minimize the maximum energy consumption among three UAVs in group n'. The constraint described in (C9-1) is that each position will be covered only once. The energy consumed by UAV group n' has an upper bound e_η in constraint (C9-2). The UAVs need to return back to the central station as described in (C9-3).

However unfortunately, Fig.5 illustrates that, there are six possible route choices for UAV to take when flying from one target to next. As the number of targets increase, the total number of possible route choices for three UAVs will grow exponentially. Thus, exhaustive search is not suggested to be performed for optimal solution.

V. HEURISTIC AND APPROXIMATION ALGORITHMS FOR SUBPROBLEM 1

In this section, two different algorithms, a heuristic algorithm and an approximation algorithm, are proposed to solve Subproblem 1, the MTSP problem.

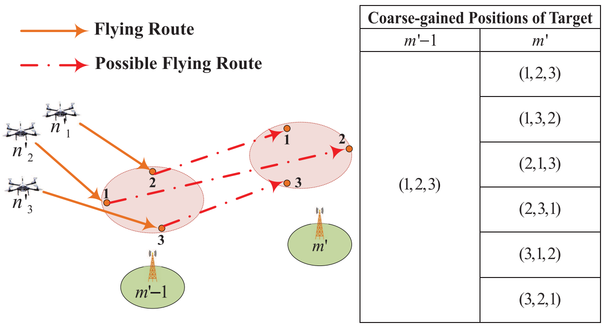


FIGURE 5. Six possible choices to fly from one target to the next. The known coarse-grained locations for the $(m' - 1)$th target along the route are labeled as 1, 2 and 3. Similarly, that for the m'th target are also labeled as 1, 2 and 3. The table lists all six possible flying options for the three UAVs. For example, the first option is to let the UAV visiting location 1 of the $(m' - 1)$th target visit location 1 of the m'th target, the UAV visiting location 2 of the $(m' - 1)$th target visit location 2 of the m'th target, and the third UAV visit location 3 of the m'th target.

A. HEURISTIC ALGORITHM

In heuristic algorithm, the classical genetic algorithm (GA) is adapted to help solve the MTSP problem [22]–[25]. The basic idea of our algorithm is to change the objective from minimizing the total cost to minimizing the maximum cost. Besides, we also add one constraint on all routes length corresponding to the all UAVs costs instead of utilizing the predefined iteration number as the only constraint on iteration times, which may reduce unnecessary iteration operations. Once the routes satisfy that they have similar length or the iteration times reach the predefined number, the result achieved will be checked to choose the best routes based on the minimum value of the maximum route cost. We use the difference value between the maximum and minimum length to justify whether the UAV flying routes have similar length. When the value is smaller than an actual value in simulation, the routes length will be justified as similar. The process of algorithm is specified in Fig. 6.

We initialize the population of routes by labeling targets as integers randomly. And then based on the number of UAV groups N', we need to select N'-1 breaking points to allocate targets to UAV groups as well as plan routes for UAV groups as illustrated in Fig.7.

With crossover and mutation operation, we then get the route populations and find the best routes among them. After evaluating the member of chosen population, we next generate new population based on evolutionary operator [22]–[25]. With the increase of iteration times, the adapted genetic algorithm can provide better performance. However, when the number of targets gets larger, the computation time increases accordingly. Therefore, we propose an approximation algorithm to guarantee low computation complexity.

B. APPROXIMATION ALGORITHM

To solve Subproblem 1, we propose an approximation algorithm, tree decomposition algorithm united with Christofides algorithm (TDCA). Before explaining and analyzing TDCA, the multi-UAV's system needs to be modeled as a complete

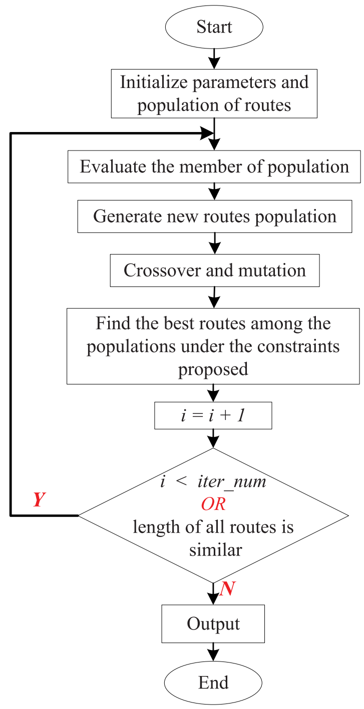


FIGURE 6. After initializing parameters and population of routes, we execute genetic algorithm operators and find the best solution among populations under the constraints of minimizing maximum route length. Once i reaches the number of iteration times or all routes has similar length, we output the best results.

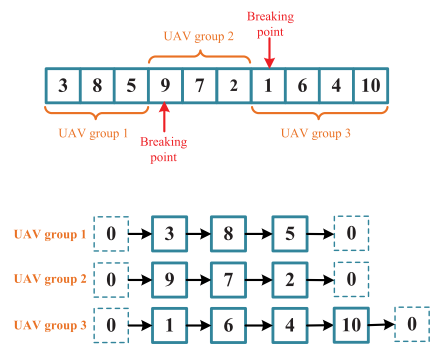


FIGURE 7. Route chromosome sequences for UAV groups. One route represent a chromosome sequence which stands for one UAV group and each gene in sequence represents one target. Take three UAV groups and ten targets as an example. Targets are labeled as integer numbers randomly. After breaking point selection, we get the UAV groups flying orders. Number 0 represents the initial position of all UAVs.

undirected graph $G = (V, E)$, where routes to be travelled are represented by edges in E and targets to be located are denoted by vertexes in V.

1) TREE DECOMPOSITION ALGORITHM

First is the tree decomposition algorithm to allocate targets to UAV groups. Before decomposing, we need to get the minimal spanning tree of G and aiming to reduce algorithm complexity, we use the delaunay triangulation to get a complete graph of graph G. And then we calculate a minimal spanning tree (MST) for preparation of forming subtrees by

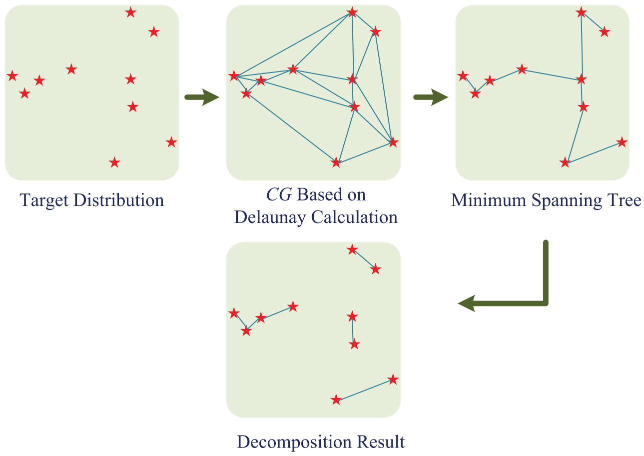


FIGURE 8. **Steps of tree decomposition algorithm. We first get the positions of all targets and a complete undirected graph *G* based on the information of target distribution. Second we compute a complete graph *CG* of *G* based on delaunay triangulation. Then we calculate the minimum spanning tree and last by deleting edges based on constraints, we get the tree decomposition result.**

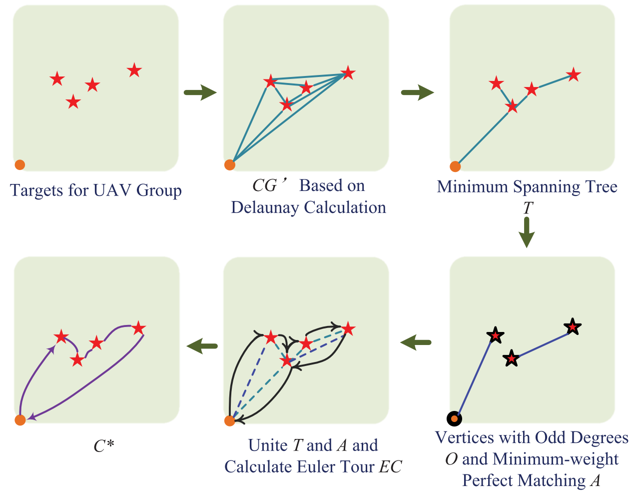


FIGURE 9. **Steps of Christofides algorithm. After allocating targets to UAV groups, we first compute a complete graph CG' based on Delaunay triangulation. Second, we calculate the minimum spanning tree T and pick out the vertices with odd degrees to form a minimum-weight perfect matching A. Then unite T and A and calculate an Euler tour EC. Finally, remove the repeated vertices and edges for the final results $C*$.**

Algorithm 1 Tree Decomposition Algorithm

Input: M, number of targets; N', number of UAV groups; $G(V, E)$;

Output: tr_n, decomposed subtree for UAV group n;

1: Compute a complete graph CG of graph G based on delaunay triangulation;
2: Calculate a minimal spanning tree mst based on the complete graph;
3: $mst' \leftarrow$ Sort the edges of mst in descent order;
4: **for** $I \leftarrow 1$ *to* $(M-1)/N'$ **do**
5:   **if** $max(cost(tr_n)) > \sum(cost(tr_n))/(N'-1)$ **then**
6:     **for** $i \leftarrow 1$ *to* $M-1$ **do**
7:       $temp = mst'(i)$, $mst'(i) = 0$;
8:       **if** $min(num(n)) > I$ **then**
9:         update mst', len, tr_n, $num(n)$;
10:       **else**
11:         $mst'(i) = temp$;
12:       **end if**
13:       **if** $len > N'$ **then**
14:         break;
15:       **end if**
16:     **end for**
17:   **else**
18:     break;
19:   **end if**
20: **end for**

deleting edges of mst under constraints. The specific steps are illustrated in Fig.8 and Alg.1 below.

In Algorithm 1, line 5 gives the most important constraint on the maximum weight of all subtrees which corresponds to the constraint on the maximum energy consumption of all UAV groups. Lines 6-14 express that we will delete the edges of minimal spanning tree in orders to form subtrees, which can be seen as allocating targets to UAV groups and once the number of subtrees reaches the number of UAV groups, the steps of subtree formation should be stopped.

Algorithm 2 Christofides Algorithm

Input: $G'(V, E)$;

Output: C^*, circuit route for UAV group n;

1: $CG' \leftarrow$ a complete graph computed by delaunay triangulation method on G';
2: $T \leftarrow$ a minimal spanning tree by calculation on CG';
3: $O \leftarrow$ vertices with odd degrees in T;
4: $A \leftarrow$ a perfect match graph of O with minimal weight;
5: $C \leftarrow A \cup T$;
6: $EC \leftarrow$ an Euler circuit calculated on C;
7: $C^* \leftarrow EC-$ repeated vertices;

2) CHRISTOFIDES ALGORITHM

Second is the approximation algorithm called Christofides algorithm to plan the trajectory for all UAV groups. The specific steps are illustrated in Fig.9 and Alg.2 below.

In Algorithm 2, lines 1 and 2 are supposed to calculate a minimal spanning tree T. Lines 3 and 4 are objected to find a minimum weight perfect match A for the odd degree vertices O in T. Lines 5-7 are to union T and A to get the final circuit route.

3) ALGORITHM ANALYSIS

We will verify the approximation ratio of the proposed approximation algorithm and analyze its time complexity in this part.

The system of multi-UAV locating multi-target is modeled as a graph G to simplify the analysis. The minimal spanning tree is represented by mst and its cost is

$W(mst) = w(mst) + p(mst)$. The subtree with maximum weight by optimal solution is marked as opt and its weight is $w(opt)$ after tree decomposition. The cost of the subtree opt is marked as $W(opt)$. The nth subtree formed by Algorithm 1 is represented by tr_n with $w(tr_n)$ weight.

Lemma 1: For Algorithm 1, subtrees after tree decomposition algorithm satisfy:

$$W(TR) \leq \frac{1}{N'-1} \sum_{n=1}^{N'} (w(tr_n) + p(tr_n)), \tag{10}$$

where $W(TR)$ represents the maximum weight of all UAV groups after Algorithm 1 allocating targets to them. We define the total weight of all edges in subtree tr_n as $w(tr_n)$ and the total weight of all vertices in subtree tr_n as $p(tr_n)$.

Proof: According to line 4 of Algorithm 1, subtrees satisfy the constraint that the total weight has an upper bound, $\frac{1}{N'-1} \sum_{n=1}^{N'} W(tr_n)$. The target points in tr_n will be joined with the central station location point. $cost(tr_n)$ is the cost of the trajectory of tr_n planned by Algorithm 2 on those points. Thus, we get

$$\begin{aligned} W(TR) &= \max_{1\leq n\leq N'} \{W(tr_n)\} \\ &\leq \frac{1}{N'-1} \sum_{n=1}^{N'} W(tr_n) \\ &= \frac{1}{N'-1} \sum_{n=1}^{N'} (w(tr_n) + p(tr_n)). \end{aligned} \tag{11}$$

■

Lemma 2: In Algorithm 2, the circuit route of the nth UAV group has an upper bound $\frac{3}{2} cost\,(p^*(tr_n))$, where $p^*(tr_n)$ is the optimal solution for nth UAV group and $cost(\cdot)$ is the cost.

Proof: The cost of minimal spanning tree of nth UAV group is smaller than the optimal trajectory, $cost(T(tr_n)) \leq cost(opt(tr_n))$. In lines 3 and 4 of Algorithm 2, the vertices of $O(tr_n)$ is less than half of the vertices of tr_n. Therefore, the cost of perfect match graph of $O(tr_n)$ is less than half of $cost(opt(tr_n))$, $cost(A(tr_n)) \leq \frac{1}{2} cost(opt(tr_n))$. Then, we get

$$\begin{aligned} cost\left(C_n^*\right) &= cost(T(tr_n)) + cost(A(tr_n)) \\ &\leq cost\left(p^*(tr_n)\right) + \frac{1}{2} cost\left(p^*(tr_n)\right) \\ &= \frac{3}{2} cost\left(p^*(tr_n)\right). \end{aligned} \tag{12}$$

■

Theorem 1: After TDCA, the maximum cost of all UAV groups, $cost(TR)$, satisfy:

$$cost(TR) \leq \frac{3}{2*(N'-1)} W(MST). \tag{13}$$

Proof: The cost of TR must be proportional to the $W(TR)$, $cost(TR) \leq \frac{1}{N'-1} \sum_{n=1}^{N'} (cost(tr_n))$ because of Lemma 1 and 2. Besides, since tr is formulated by deleting edges from MST, the weight of MST is bigger than the total cost of $opt(tr_n)$. The theorem is proved as follows:

$$\begin{aligned} cost(TR) &= \max_{1\leq n\leq N'} (cost(tr_n)) \\ &\leq \frac{1}{N'-1} \sum_{n=1}^{N'} (cost(tr_n)) \\ &\leq \frac{3}{2*(N'-1)} \sum_{n=1}^{N'} (cost(opt(tr_n))) \\ &\leq \frac{3}{2*(N'-1)} W(MST). \end{aligned} \tag{14}$$

■

The lower bound of $cost(max)$ denoting the maximum cost of the optimal solution P^* is proved to make an analysis on the approximation ratio of the proposed approximation algorithm.

Lemma 3: Let opt be the optimal trajectory graphs for UAV groups, max be the trajectory graph with maximum cost achieved by the optimal solution and $cost(max)$ be the maximum cost of the UAVs' trajectories by optimal solution. It holds that

$$cost(max) \geq \frac{1}{N'} W(MST). \tag{15}$$

Proof: The basic theories of Lemma 2 are that the maximum cost is bigger than the average and the cost of minimal spanning tree is smaller than the cost of P^*. Then, we get

$$\begin{aligned} cost(max) &= \max_{1\leq n\leq N'} \left\{cost(P_n^*)\right\} \\ &\geq \frac{1}{N'} \sum_{n=1}^{N'} \left\{cost(P_n^*)\right\} \\ &\geq \frac{1}{N'} W(MST). \end{aligned} \tag{16}$$

■

Theorem 2: The approximation ratio of the proposed algorithm, TDCA is $\frac{3*N}{2*(N-1)}$.

Proof: Combining *Theorem 1* with *Lemma 3*, we get

$$\begin{aligned} cost(TR) &= \max_{1\leq n\leq N'} \{cost(tr_n)\} \\ &\leq \frac{3}{2*(N'-1)} W(MST) \\ &\leq \frac{3*N'}{2*(N'-1)} cost(max). \end{aligned} \tag{17}$$

■

Theorem 3: The proposed approximation algorithm TDCA for the UAVs trajectory planning problem takes $O(n^3)$ time, with a metric complete graph $G = (V, E)$ and a positive integer N' taken into consideration.

Proof: TDCA is a union of tree decomposition algorithm and Christofides algorithm. We first analyze the time complexity of tree decomposition algorithm, which includes two main steps, the calculation of MST and the formation of subtrees. The time taken to calculate an MST is $O(n^2)$ while the time consumed to get the subtrees is also $O(n^2)$ corresponding to Algorithm 1. Thus the time complexity of tree decomposition algorithm is $O(n^2)$. Then Christofides algorithm is also divided into two parts, calculating the MST and finding a minimum weight perfect match for odd degree vertices. Calculating the MST costs $O(n^2)$ time and finding the minimum weight perfect match consumes $O(n^3)$, which contributes to the $O(n^3)$ time complexity for Christofides algorithm [27]. Thus, the time complexity of tree decomposition algorithm united with Christofides algorithm is proved to be $O(n^3)$. ∎

In summary, the approximation ratio of the proposed approximation algorithm, tree decomposition algorithm united with Christofides algorithm for Subproblem 1 is testified as $\frac{3*N'}{2*(N'-1)}$ where N represents the number of UAVs, and its time complexity is proved to be $O(n^3)$.

VI. A HEURISTIC ALGORITHM FOR SUBPROBLEM 2

In this section, a two-step greedy heuristic algorithm is proposed for subproblem 2.

As shown in Fig.5, there are six possible route choices for UAV to fly from one target to next. As the the number of targets increases, the total number of possible routes for these three UAVs will grow exponentially, which makes it impossible to perform exhaustive search for optimal solution. To this end, a two-step greedy heuristic algorithm is proposed.

1) The routes for three UAVs locating adjacent targets are planned greedily. Routes are all divided into segments, each of which represents the UAV flying from one target to another. For each segment, we need to pick out the route choice which costs minimum energy. We can complete the selection process in constant time due to the finite 6 possible route choices. After we determining the routes on all route segments, they will be concatenated to form entire flying routes. We specify the algorithm below.

In Algorithm 3, we need to input the number of targets, the coarse-grained positions around these targets and the flying choices in each route segment. Lines 5-7 are to find the maximum route length of the UAV group in each segment denoted by d_{max}. Lines 4-8 are to select the minimum value of d_{max}, which has 6 values representing the route lengths of 6 choices. In line 10, we record the coordinates for each of the three UAVs in one group to fly through in the ith segment.

2) Local adjustments are operated on the routes of each segment. When one segment is adjusted, we keep the route choices of the rest segments invariable. If the adjustment taken brings smaller maximum energy consumption, we will accept it and turn to the next segment. The final output combined with all these adjustments is the solution for Subproblem 2. We detailedly introduce the algorithm in Algorithms 4.

Lines 5-7 store the maximum route length of three UAVs in one group denoted by D_{max}. The minimum route length is chosen in line 8 with decision on the route choice based on the value of D_{min}. In line 10, the coordinates are recorded for each of the three UAVs to fly through in the ith segment.

Algorithm 3 Initial Route Planning Algorithm

Input: m, number of targets; x, y, two $m \times 3$ matrices of targets' locations; ach, 6 possible flying route choices
Output: ind_1, an array to choose choices from ach; X_1, Y_1, two $m \times 3$ matrices of three UAVs' coordinates;
1: **for** $k \leftarrow 1$ *to* 3 **do**
2: $X_1(1,k) \leftarrow x(1,k)$, $Y_1(1,k) \leftarrow y(1,k)$;
3: **end for**
4: **for** $i \leftarrow 1$ *to* $m-1$ **do**
5: **for** $j \leftarrow 1$ *to* 6 **do**
6: $d_{max}(j) \leftarrow$ the maximum route length of the ith segment from three UAVs choosing route $ach(j)$;
7: **end for**
8: $d_{min}(i) \leftarrow$ the minimum value of d_{max}, $ind_1(i) \leftarrow$ the index of chosen route from ach based on $d_{min}(i)$;
9: **for** $k \leftarrow 1$ *to* 3 **do**
10: $X_1(i+1,k) \leftarrow x(i+1, ach(ind_1(i),k))$, $Y_1(i+1,k) \leftarrow y(i+1, ach(ind_1(i),k))$;
11: **end for**
12: **end for**

Algorithm 4 Local Adjustment Algorithm for Routes

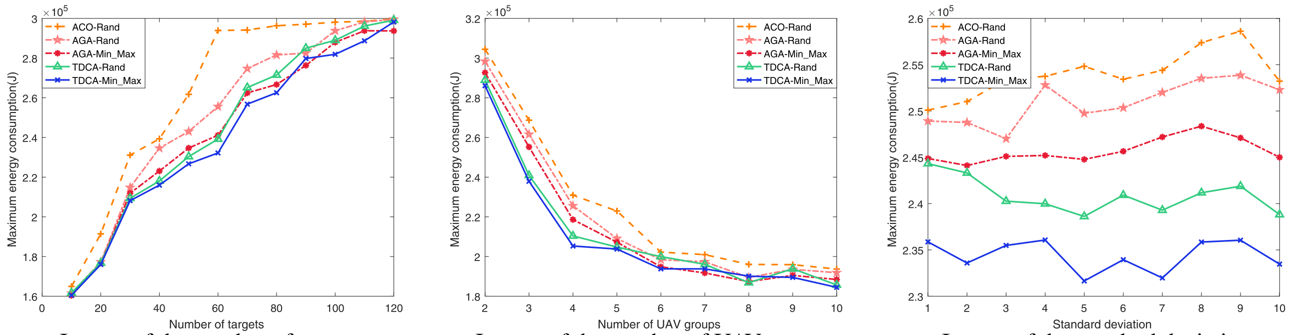
Input: m, number of targets; x, y, two $m \times 3$ matrices of targets' locations; ind_1, an array from Algorithm 1
Output: ind_2, an array to choose choices from ach; X_2, Y_2, two $m \times 3$ matrices of three UAVs' coordinates;
1: **for** $k \leftarrow 1$ *to* 3 **do**
2: $X_2(1,k) \leftarrow x(1,k)$, $Y_2(1,k) \leftarrow y(1,k)$;
3: **end for**
4: **for** $i \leftarrow 1$ *to* $m-1$ **do**
5: **for** $j \leftarrow 1$ *to* 6 **do**
6: $D_{max}(j) \leftarrow$ the maximum value of summarizing all segments' length based on $ach(j)$, ind_1 and ind_2 of three UAVs;
7: **end for**
8: $D_{min}(i) \leftarrow$ the minimum value of $D_{max}(j)$, $ind_2(i) \leftarrow$ the index of chosen route from ach based on $D_{min}(i)$;
9: **for** $k \leftarrow 1$ *to* 3 **do**
10: $X_2(i+1,k) = x(i+1, ach(ind_2(i),k))$, $Y_2(i+1,k) = y(i+1, ach(ind_2(i),k))$;
11: **end for**
12: **end for**

VII. PERFORMANCE EVALUATION

The performances of the proposed two algorithms will be evaluated in this section.

A. SIMULATION SETUP

We assume the surveillance area to be a square region and its side length to be $5km$. The targets are subject to Poisson distribution as illustrated in Fig.12 below. The targets are all within the square region. The distribution of the coarse-grained positions around the targets is subject to uniform distribution within a circle range around the targets. The radius of the circle depends on the constraint on measurement range which



(a) Impact of the number of targets (b) Impact of the number of UAV groups (c) Impact of the standard deviation

FIGURE 10. Impacts of different factors on maximum energy consumption.

TABLE 2. Simulation parameters.

Parameters	Area size	H_0	e_{mo}	e_p	e_η
Values	$5 \times 5km^2$	$100m$	$13.19J/m$	$308.71J$	$300kJ$

is set to $100m$ in simulation. UAVs are all based at $(0, 0, 0)^T$ and flying at the height of $100m$. Referred to the motion energy consumption parameter in [23], the energy consumed per unit horizontal distance e_{mo} will be set to $13.19J/m$. The positioning energy consumption e_p is set to $308.71J$ according to the $308.71W$ horizontal power consumption [24]. The energy bound e_η will be set to $300kJ$ in this section. The configuration is listed in Table 2.

The proposed two algorithms, marked as TDCA-Min_Max and AGA-Min_Max, will be compared with algorithms as follows.

- ACO-Rand: this algorithm utilizes ant colony optimization algorithm to settle the MTSP problem and then allocates the three positions to a UAV group in random order.
- AGA-Rand: this algorithm solves the MTSP problem with adjusted genetic algorithm (AGA) and then also allocates the three positions to a UAV group randomly.
- TDCA-Rand: this algorithm solves the MTSP problem with TDCA and then randomly allocates the three positions to a UAV group in random order.

B. SIMULATION RESULTS

Four sets of simulations are performed to specify the performance of the proposed algorithms in this section. To get the result of one simulation point, several simulations will be performed for average value. For example, for targets less than 60, we perform about 100 times simulations for each simulation point and for targets more than 60, about 50 or less times of simulations will be performed according to the actual time consumption. The time used for performing one simulation on different numbers of targets is shown in Table 3. Table 3 shows that with the increase of number of targets, the computation time of TDCA-Rand remains stable while the computation time of ACO-Rand and AGA-Rand increase greatly because of the increase of iteration time to achieve the same performance as TDCA-Rand. Thus, the computation time is reduced effectively by our proposed TDCA algorithm compared with the ant colony optimization algorithm and genetic algorithm.

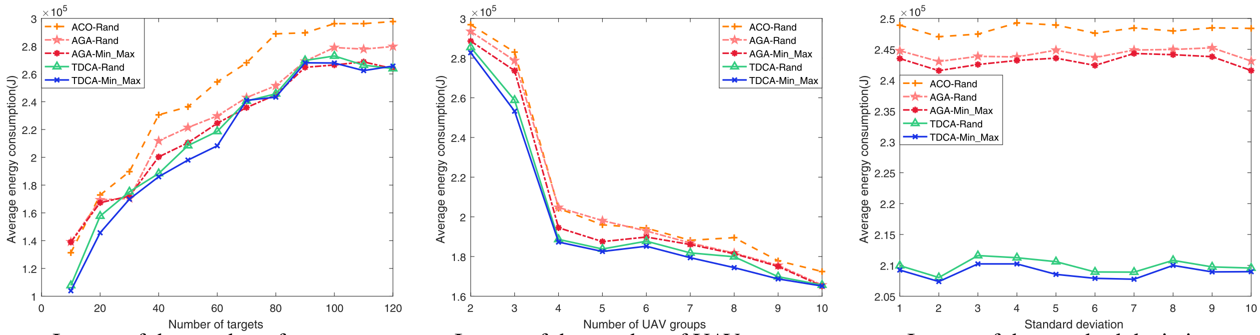
TABLE 3. Computation time.

Number of targets	10	20	60	120
Time of ACO-Rand/s	9.618	20.978	514.963	46926.169
Time of AGA-Rand/s	8.034	17.403	629.316	54032.574
Time of TDCA-Rand/s	6.991	7.707	8.291	9.037

1) IMPACT OF NUMBER OF TARGETS

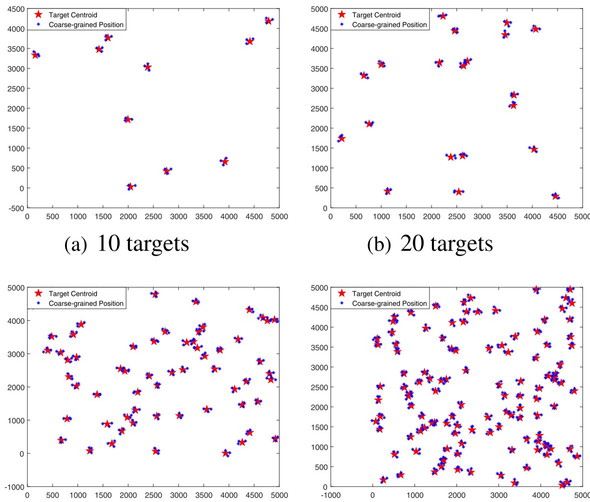
First, the number of UAV groups is set to 4. As the number of targets increases from 10 to 120, the maximum energy consumption trends of five algorithms are shown in Fig. 10(a). The maximum energy consumption will be reduced by $0.6\% - 26.6\%$ with the proposed algorithms marked as TDCA-Min_Max and AGA-Min_Max. When the number of targets is 10 or 120, our proposed algorithms can reduce only 0.6% and 0.7% respectively for two different reasons. The first is that, the differences between the number of targets allocated to UAVs by different algorithms are minor when the number of targets is small. The other is that, when the number of targets reaches 120, the maximum energy consumptions of different algorithms all reach the limitation, e_η, which makes their differences minor as the same. Besides, when the number of targets is 60, the energy consumed by our proposed algorithm can reduce up to 26.6% maximum energy consumption. And it also can be reduced by $0.5\% - 24.9\%$ with the proposed heuristic algorithm marked as AGA-Min_Max. As the number of targets increases, the maximum energy consumption of our proposed algorithm is evidently increasing much more slowly than the others.

Fig. 11(a) illustrates that the TDCA-Min_Max algorithm will reduce $1.4\% - 26.3\%$ of the average energy consumption and the AGA-Min_Max algorithm will reduce $0.6\% - 11.8\%$ of the average energy consumption, which suggests that the proposed two algorithms will also be able to reduce the total energy consumption of all UAVs. Compared with the results of ACO-Rand, AGA-Rand and



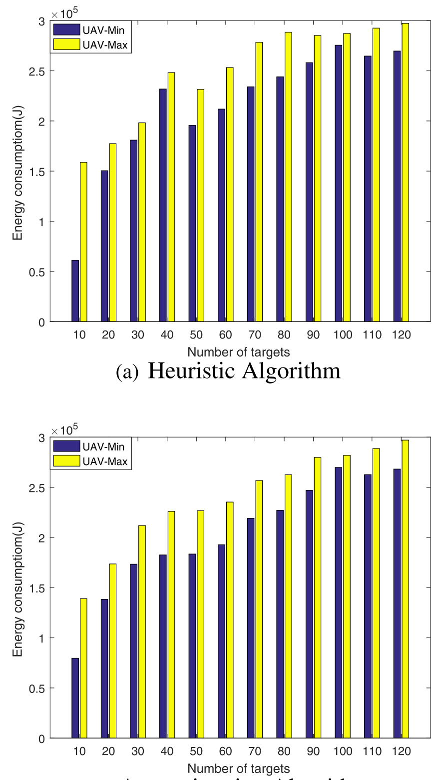
(a) Impact of the number of targets (b) Impact of the number of UAV groups (c) Impact of the standard deviation

FIGURE 11. Impacts of different factors on average energy consumption.



(a) 10 targets (b) 20 targets (c) 60 targets (d) 120 targets

FIGURE 12. Distributions of different numbers of targets.



(a) Heuristic Algorithm

(b) Approximation Algorithm

FIGURE 13. Maximum and minimum energy consumption of UAVs.

TDCA-Rand algorithm, our proposed algorithms perform better in MTSP problem. Besides, comparing AGA-Rand with AGA-Min_Max and TDCA-Rand with TDCA-Min_Max respectively, our proposed step-greedy algorithm performs effectively in Subproblem 2.

2) IMPACT OF NUMBER OF UAV GROUPS

Second, the number of targets is set to 60. As the number of UAV groups increases from 1 to 10, it is shown in Fig. 10(b) that the maximum energy consumption has a trend to decrease and in Fig. 11(b) that the average energy consumption also decreases. When n', the number of UAV groups, reaches 4, the maximum as well as average energy consumptions of all algorithms drop slowly with the increase of n'. Therefore, we are not supposed to set n' to a high one for lower energy consumption. In practice, we should choose the number economically.

3) IMPACT OF STANDARD DEVIATION

Third, fix the numbers of UAVs and targets as well as the position of the targets while the distributions of positions surrounding the targets are different. The maximum and average energy consumption trend of five algorithms are illustrated in Fig. 10(c) and Fig. 11(c), respectively. The number of UAV groups is set to 4 and the targets are 60. After solving Subproblem 1, the targets are allocated to the UAV groups and the result is fixed when the distribution of the positions is changing. It turns out that the adjusted GA and TDCA can effectively minimize the energy consumption of each UAV, and the maximum energy consumption among all UAVs can be effectively reduced by the two-step greedy heuristic algorithm proposed in Section VI.

4) MAXIMUM AND MINIMUM ENERGY CONSUMPTION

Finally, Fig.13 reveals the maximum and minimum energy consumption trends of all UAVs. As illustrated in this figure, the energy gap between the UAVs consuming maximum energy and minimum energy is small, which proves that the two algorithms we propose, TDCA-Min_Max and AGA-Min_Max, can provide balanced energy consumption among all UAVs. With the number of targets increasing, the energy gaps between UAVs consuming maximum and minimum energy are smaller in Fig.13(b) than in Fig.13(a), proving the more stable performance of approximation algorithm TDCA than heuristic algorithm AGA.

VIII. CONCLUSION

Planning trajectory for UAVs which perform trilateration on mobile targets with limited energy is considered in this paper. We formulate the problem with intention to minimize the maximum energy consumption among all UAVs. To solve it, we decompose this problem into two subproblems by dividing UAVs into groups each of which has three UAVs. We consider Subproblem 1 as an MTSP problem, and propose two different algorithms, a heuristic algorithm and an approximation algorithm with approximation ratio of $(1.5 * (N'/(N'-1)))$, to solve it. Then, a two-step greedy heuristic algorithm is proposed to achieve a sub-optimal solution for Subproblem 2. The calculation time and computation complexity is effectively lowered by the approximation followed by a greedy algorithm. Through extensive simulations, it turns out that compared to methods choosing routes for UAVs randomly, our proposed approaches are more efficient and the approximation followed by greedy algorithm can reduce up to 26.6% maximum energy consumption while the heuristic followed by greedy algorithm can reduce up to 24.9% maximum energy consumption. In future work, we will focus on an approximation or other better heuristic algorithm to solve Subproblem 2.

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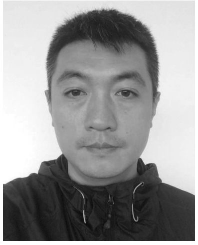

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