Minimizing Data Collection Time With Collaborative UAVs in Wireless Sensor Networks

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ABSTRACT Unmanned aerial vehicle (UAV) data collection is a promising research direction that can be applied to many practical scenarios. Due to the limited energy of sensors in wireless sensor networks (WSN), UAV, which is considered as a mobile fusion center, can effectively prolong the lifetime of sensor via supporting communication with the sensor directly. However, since the UAV's energy constrained, it is necessary that multiple UAVs provide data collection to sensors in large areas. In this paper, we consider a scenario where multiple UAVs collect data from a set of two-dimensional distributed sensors. The UAV can communicate with sensors while flying or hovering. The goal is to minimize the total time that all UAVs from data center and return to data center after completing all collection tasks, while giving each sensor a certain amount of data and energy. The problem of minimizing the task completion time of multiple UAVs is still a big challenge. We solve the multi-UAV problem by jointly optimizing UAV-sensor association mechanism and data collection method of UAVs. The numerical results show that the proposed multi-UAV data collection scheme shortens the task completion time.

INDEX TERMS UAV, data collection, trajectory optimization, traveling salesman problem.

I. INTRODUCTION

Recently, wireless communication in wireless sensor networks (WSN) by leveraging the use of unmanned aerial vehicles (UAVs) has attracted a wide range of attention [1]–[8]. On the one hand, UAVs can expand network coverage and enhance system capacity due to UAV's high mobility [9]. On the other hand, it has higher chance of line-of-sight (LoS) communication links to terrestrial sensors due to high altitude of UAV, which can further provide reliable downlink and uplink communications to sensors [10]. One of the most important applications is the use of UAVs for data collection to improve efficiency and reliability. UAVs can fly to wireless sensors to provide data communication directly, which avoids delivering data to a fusion center

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by multi-hop transmission and greatly prolongs the lifetime of sensors. Moreover, battery power of UAV is limited, while UAV's energy is mainly used to support flight. If we only use one UAV to collect data from a large number of sensors, UAV may not have enough energy to complete the collection task. Hence, multi-UAV data collection gradually became a hot research issue at present [11].

A. RELATED WORK

To collect data efficiently by UAV, the authors of [12] optimize UAV deployment and trajectory jointly via quantization theory approach. The authors of [13] introduced a UAV's data collection strategy during hovering for the purpose of minimizing data delay by utilizing controllable channel variations. The authors of [14] sought to maximize throughput when a UAV flying from source sensor node to destination sensor node, however, the distribution of sensor nodes is assumed

to be a straight line, which is unrealistic in actual scene. The authors of [15] investigated data collection scheme to reduce multi-sensor interference via adjusting UAV heading and beamforming. The authors of [16] proposed a UAV data collection mechanism to minimize flight time by dynamic programming (DP) algorithm in the case of one-dimensional distribution of sensors without consider data collection order of sensors. These works are limited to a single UAV to provide data collection in a static sensor networks, and do not consider sensors with the random two-dimensional spatial distribution. Meanwhile, the existing data collection mechanisms also limit to flying or hovering mode only.

Different from single-UAV data collection schemes, there is a UAV-sensor association issue for multi-UAV data collection scheme. In actual application scenario, single-UAV data collection system can not cope with the excessive number of wireless sensors [17]. One of the most important challenges in multi-UAV data collection system is how to improve the system transmission rate while ensuring the fairness of user association mechanism [18]. There are some classical UAV-sensor association methods such as Voronoi diagrams [19] which only considered the spatial distance between UAVs and terrestrial sensors. In Voronoi diagram, the density and actual demand of users are not taken into account. As a consequence, Voronoi diagram can be highly congested with users or result in waste of resource. Reference [20] added the signal-to-noise ratio (SINR) constraint, which is more in line with actual communication scenario, but still does not consider the congestion problem caused by spatial distribution and actual demand of users. The work in [21] presented a user demand based network model using multiple UAVs for providing better capacity. However, this study only considered the scene where users are uniform distributed. In addition, the above articles don't consider the channel model in actual communication scenario and differences between sensors, such as sensors' location and amount of data. Moreover, there is no further research on data collection scheme combining with UAV-sensor association mechanism.

It is worthwhile to note that existing works do not consider UAV energy consumption and load issues. It is very practical to formulate multi-UAV data collection methods to effectively shorten the data collection time of UAVs. In this paper, we present a multi-UAV collaborative data collection algorithm to minimize task completion time by designing a reasonable UAV-sensor association scheme and jointly optimizing collection position, UAVs' flight speed and sensors' transmit power.

B. CONTRIBUTIONS

In particular, we consider a network in which multiple UAVs are deployed as aerial base stations to collect data from a set of energy constrained ground sensors that are randomly distributed over a geographical area. Each sensor has a certain amount of data to be uploaded to UAV. UAVs can choose two data collection modes based on actual conditions: flying and hovering. Flying mode means UAV will fly to specific

position and collect data with another speed. Hovering mode means UAV will fly to sensor and then hover over it to collect data. We define the data collection completion time as longest flight time among all UAVs. The goal is to minimize task completion time and the main contributions lie in three aspects:

(1) We design a fair partition algorithm for our multi-UAV data collection system to reduce the number of WSN sensors associated with each UAV, the problem of minimizing the utility function is proposed while considering the fairness of user association mechanism. Each wireless sensor is served by the optimal UAV via our partition algorithm. The mechanism of association between UAVs and sensors is determined, so multi-UAV flight time of data collection minimization problem can be transformed into multiple single-UAV data collection problems, so as to reduce complexity of optimization problem.

(2) We solved the problem of minimizing flight time for multiple sensors associated with one UAV. Since data collection has two modes: flying mode and hovering mode, we compare the flight time of two modes to determine which collection mode is currently used. As a consequence, we obtain the collection mode with shortest flight time. Combined with proposed UAV-sensor association scheme, the multi-UAV collaboration system in wireless sensor network that minimizes collection time is solved efficiently.

(3) In order to verify the performance of our multi-UAV data collection system, we also conducted a series of simulations. The results highlight the contrast between our UAV data collection system and the baseline algorithm, with significant improvements in flight time, fairness, etc.

The rest of this paper is organized as follows. Section II presents the system models and formulates the optimization problem. Section III and section IV give the method to solve the problem. The simulation results are given in section V. Finally, Section VI concludes the paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION
A. SYSTEM MODEL

As shown in Fig. 1, we consider the uplink environment of ground-to-air network within which M UAVs provide communication services for N energy-limited WSN sensors which denote as $\mathcal{M} = \{1, 2, \ldots, M\}$ and $\mathcal{N} = \{1, 2, \ldots, N\}$, respectively. sensors are randomly distributed in two-dimensional geographical area and carry a certain amount of data that needs to be uploaded. UAVs are assumed to have fixed altitude H. Each sensor j ($j \in \mathcal{N}$) needs to upload B_j information bits within a total energy budget E_j. Let $(X_i(t), Y_i(t), H)$ be the three-dimensional coordinate of each UAV i ($i \in \mathcal{M}$) at time t and (x_j, y_j) be the location of each sensor j. We assume W be total available bandwidth. In this model, geographical area is divided into M partitions by using Voronoi diagram. We use variable a_{ij} to represent association of sensor j with UAV i, where $a_{ij} = 1$ represents sensor j is served by UAV i,

| Notation	Definition
$p_{\text{LoS}}^{ij}(t)$	the probability of LoS
$L_{dB}(t)$	mean path loss
$\gamma_{ij}(t)$	the received signal-to-noise for sensor j connected to UAV i
$R_{ij}(t)$	data rate of sensor j served by UAV i
$d_{ij}(t)$	time-varying distance between sensor j and CP
$t_{jk_{fu}i}$	flight time of UAV i used in collecting data
$t_{jk_{hu}i}$	data transmission time of UAV i used in collecting data
$t_{jk_{nu}i}$	time used in only flying
$\boldsymbol{T}$	UAV collection sequence
$\boldsymbol{S}$	collection mode vector
$\boldsymbol{P}$	sensor transmit power vector
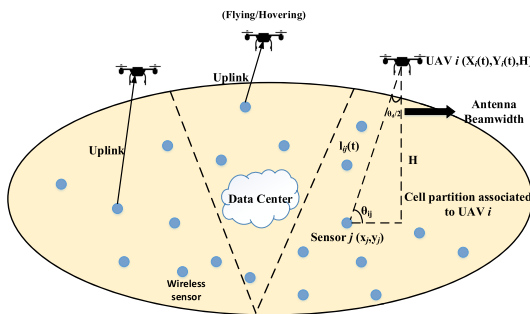
FIGURE 1. System model.

whereas $a_{ij} = 0$. Hence, terrestrial sensors are divided into M disjoint partitions each of which is associated with one of UAVs. The set $\mathcal{A} = \{a_{ij}|i \in \mathcal{M}, j \in \mathcal{N}\}$ represents association scheme between WSN sensors and UAVs. Sensors associated with UAV i are denoted as the set of $\mathcal{K}_i$ with size K_i, where K_i is the number of sensors that are served by UAV i. Each sensor is only served by one UAV. UAVs can choose to fly or hover to collect data of sensors based on actual conditions.

1) GROUND-TO-AIR PATH LOSS MODEL
Statistical channel model is chosen in this paper. Position of UAVs is time-varying, so the probability of LoS is [18]

$$p_{\text{LoS}}^{ij}(t) = \frac{1}{1 + \psi \exp\left(-\beta\left[\theta_{ij}(t) - \psi\right]\right)}, \quad (1)$$

where ψ and β are constant values reflecting environment impact, $\theta_{ij}(t) = \frac{180}{\pi} \times \sin^{-1}\left(\frac{H}{l_{ij}(t)}\right)$ is elevation angle between UAV i and sensor j, where $l_{ij}(t) = \sqrt{\left(X_i(t) - x_j\right)^2 + \left(Y_i(t) - y_j\right)^2 + H^2}$ is distance between UAV i and terrestrial sensor j. The probability of non-line-of-sight (NLoS) is $p_{\text{NLoS}}^{ij}(t) = 1 - p_{\text{LoS}}^{ij}(t)$.

Also, $L_{dB}(t)$ is mean path loss which for ground-to-air communication can be formulated as [19]

$$L_{dB}(t) = \left(\frac{4\pi f_c}{c}\right)^2 l_{ij}^{\alpha}(t)\left[p_{\text{LoS}}^{ij}(t)\mu_{\text{LoS}} + p_{\text{NLoS}}^{ij}(t)\mu_{\text{NLoS}}\right], \quad (2)$$

where f_c is UAV's carrier frequency, c is speed of light, α is pathloss exponent. μ_{LoS} and μ_{NLoS} are average

additional loss to the free space propagation for LoS and NLoS connection, depending on environment respectively.

Hence, UAV i received signal power from sensor j can be given by

$$P_{ij}(t) = \frac{P_j(t)}{L_{dB}(t)}, \quad (3)$$

where $P_j(t)$ is sensor's transmit power. Considering noise power is σ^2, the received signal-to-noise for sensor j connected to UAV i is

$$\gamma_{ij}(t) = \frac{P_j(t)}{L_{dB}(t)\sigma^2}. \quad (4)$$

Now, using Shannon formula, data rate of sensor j served by UAV i can be given by

$$R_{ij}(t) = \frac{W}{M} \log_2\left(1 + \gamma_{ij}(t)\right), \quad (5)$$

where W is equally divided among UAVs so as to eliminate interference between UAVs.

2) DATA COLLECTION MODEL
UAVs are dispatched to collect data from N two-dimensional distributed sensors and then fly back to data center. A UAV only provides communication service for one sensor at a time. When UAVs only hover in the air, the channel environment may not always be good for every sensor, since distance between the sensor and its associated UAV can be large. And some sensors can not upload all of data to UAV within constrained energy due to bad channel environment. So we consider letting that UAVs choose to fly or hover to collect data based on actual conditions.

We assume that all UAVs fly with constant speed $0 \le v \le v_{\max}$. If UAVs do not need to collect data from sensors, they will fly with maximum speed v_{max} to minimize flight time.

Note that if a UAV choose flying mode means UAV will choose a collection position (CP) at first, then UAV will fly with v_{max} to CP and start to collect data with another speed which ensures that data can be collected when UAV flies over the sensor. And hovering mode does not mean UAV hover in its initial position, UAV will fly with v_{max} to sensor and then hover over it to collect data since a better channel environment can be obtained. We give specific form of the two modes as following:

(1) Data collection on flying mode: Assume that UAV i need to collect data from sensor j, the horizontal distance between sensor j and UAV i is x_{ij} and horizontal distance between CP of sensor j and UAV i is x_{ij}^{cp}. Then UAV flies with speed v_{ij} from CP to sensor j and the time-varying distance between sensor j and CP can be expressed as

$$d_{ij}(t) = \sqrt{\left(x_{ij} - x_{ij}^{cp} - v_{ij}t\right)^2 + H^2}. \quad (6)$$

Let $x_j^{cp} = x_{ij} - x_{ij}^{cp}$ representing horizontal distance between CP and sensor j. The flight time is $t_{ij} = \frac{x_j^{cp}}{v_{ij}}$, so there is

$$\int_0^{t_{ij}} P_j(t)dt \le E_j. \tag{7}$$

To ensure that all of data can be uploaded, the data upload constraint must be satisfied

$$\int_0^{t_{ij}} R_{ij}(t)dt \ge B_j. \tag{8}$$

(2) Data collection on hovering mode: When UAV i flies over sensor j, a constant transmit power and rate can be obtained since the transmission link is static. Sensor j's energy constraint can be written as

$$T_j \times P_j \le E_j, \tag{9}$$

where T_j is data transmission time.

To ensure that all of data can be uploaded, data upload constraint in hovering mode also can be given by

$$\frac{W}{M} T_j \log_2(1 + \frac{\gamma_{ij}}{T_j}) \ge B_j. \tag{10}$$

Note that which mode is better determined by many factors such as information bits, energy constraint and etc, so the best strategy is to dynamically select two modes based on actual conditions.

B. PROBLEM FORMULATION

We define task completion time as flight time used by the UAV which flies back to data center at the latest. To solve this problem, we need to determine UAV-sensor association mechanism and obtain the flight time of all UAVs. Note that flight time for each UAV is independent of other UAVs, so we present the optimization problem which is called (**OP**) to find UAV-user association scheme, collection sequence, collection position, UAVs' flight speed, and sensors' transmit power as

(**OP**) :

$$\arg[\min_{\boldsymbol{S}} \min_{\boldsymbol{T},\boldsymbol{x},\boldsymbol{v},\boldsymbol{P}} \max_{i \in \mathcal{M}} (\sum_{j,k=1}^N a_{jk}^i((1-s_j)(t_{jk_{fu}i} + t_{jk_{nu}i})$$
$$+ s_j(t_{jk_{hu}i} + t_{jk_{nu}i})))] \tag{11a}$$

$$s.t.\ s_j \in \{0, 1\}, \tag{11b}$$

$$a_{jk}^i \in \{0, 1\}, \quad \forall i \in \mathcal{M}, j, k \in \mathcal{N}, \tag{11c}$$

$$\sum_{i=1}^M \sum_{k=1}^N a_{jk}^i = 1, \quad \forall i \in \mathcal{M}, k \in \mathcal{N}, \tag{11d}$$

$$(7) and\ (8), \quad \forall i \in \mathcal{M}, \forall j \in \mathcal{K}_i, \tag{11e}$$

$$P_j(t) \ge 0, \quad \forall j \in \mathcal{K}_i, \tag{11f}$$

$$0 \le d_j^{cp} \le d_{ij}, \forall i \in \mathcal{M}, \quad \forall j \in \mathcal{K}_i, \tag{11g}$$

$$0 \le v_{ij} \le v_{\max}, \forall i \in \mathcal{M}, \quad \forall j \in \mathcal{K}_i, \tag{11h}$$

where $t_{jk_{fu}i}$ is flight time of UAV i used in collecting data from sensor j, $t_{jk_{hu}i}$ is data transmission time of UAV i used in
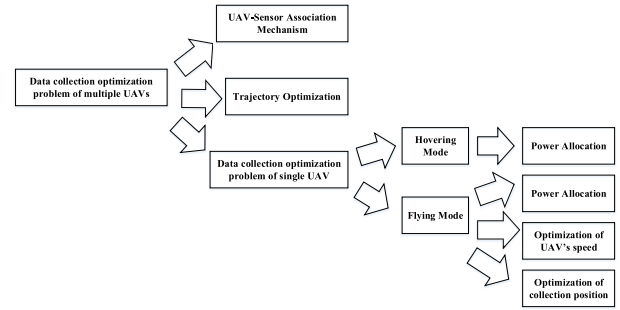

FIGURE 2. Diagram of our steps.

collecting data from sensor j while the last sensor is sensor k in hovering mode, $t_{jk_{nu}i}$ is time used in only flying. $\boldsymbol{T}$ is the UAV collection sequence and UAV-sensor association vector with each element $a_{jk}^i = 1$ representing UAV i collects data from sensor j which last senor collected by UAV i is sensor k, whereas $a_{jk}^i = 0$. $\boldsymbol{S}$ is collection mode vector with each element s_j being the collection mode of sensor j, where $s_j = 1$ represents the information of sensor j is collected by hovering mode, $s_j = 0$ represents the information of sensor j is collected by flying mode. $\boldsymbol{x}$ is the collection position vector with each element d_j^{cp} being horizontal distance between collection position and sensor j, $\boldsymbol{v}$ is flight speed vector with each element v_{ij} being UAV i flight speed from CP to sensor j, $\boldsymbol{P}$ is sensor transmit power vector with each element $P_j(t)$ being the transmit power of sensor j.

Note that (**OP**) requires optimizing the UAV collection sequence and UAV-sensor association $\boldsymbol{T}$, UAV flight speed vector $\boldsymbol{v}$, sensor transmit power $\boldsymbol{P}$ as well as the collection position $\boldsymbol{x}$, which are continuous function and binary function with respect to time t, respectively. Therefore, (**OP**) consists of an infinite number of optimization variables. In addition, the non-convex constraints in (8) include complicated functions involving a integral with the upper limit given by task completion time of single UAV. Therefore, the mixed-integer non-convex problem (**OP**) is difficult to be optimally solved efficiently.

In the following, we first propose a UAV-sensor association mechanism and collection sequence mechanism by leveraging the Multiple Traveling Salesman Problem (MTSP), and turn the collection task brought by a large number of sensors into multiple asynchronous collection tasks completed by several UAVs in Section III. Next we solve the collection time optimization problem of single UAV in Section IV. The diagram of our steps is shown as Figure.2.

III. UAV-SENSOR ASSOCIATION MECHANISM

We design a multi-UAV data collection system, however the computation of (11) is extremely difficult for even a small-scale UAVs system. So,we decompose (**OP**) into two subproblems that will be solved iteratively. We distribute a large number of collection tasks to several UAVs to shorten overall task completion time. Firstly, we consider to determine a UAV-sensor association mechanism and collection

sequence mechanism, and turn the collection task brought by a large number of sensors into multiple asynchronous collection tasks completed by several UAVs. Secondly, we optimize the collection time of each UAV separately to achieve the goal of minimizing collection task completion time. In the following section, we will illustrate the proposed framework to solving the problem.

In order to reduce the data collection time of multiple UAVs, we need to develop a fair UAV-sensor association scheme that will shorten the total flight distance of UAVs while ensuring fairness, because we must ensure that the workload of each UAV is close, that is there will be no situation where a UAV serves too many sensors.

In this case, each sensor is associated to one UAV and only communicates with the associated one. And in this subsection we assume that UAVs are in the data center at t_0 and sensors' power is given.

It can be seen that the optimization problem mentioned in this subsection is similar to the MTSP, and we intend to solve it based on MTSP. Firstly, the basic concept of MTSP is briefly reviewed as follows.

A. BRIEF INTRODUCTION TO MTSP

Traveling Salesman Problem (TSP) is a classic combinatorial optimization problem, which is used to solve a specific type of optimization problem. But sometimes, this type of optimization problem could not be defined as a classic TSP problem, which involves the assignment and optimization of multiple tasks and multi-persons. MTSP is more complicated than the TSP problem, which indicates that it is much harder to solve. Under these circumstances, the research on the MTSP is much less than that of the TSP. The MTSP problem indicates that m travel salesmen start from the same city (or different cities) and take a travel route. Each city will be passed for only one time (except the departure city), and the total distance is the shortest. The problems related to MTSP are widely used in real life, such as: transportation, pipeline laying, route selection, computer network topology design, postal delivery line planning, etc.

Mathematical description of the traditional MTSP model: There are m travel salesmen who need to visit n cities ($n > m$), so that l_{jk} denotes the distance between the city c_j and c_k. Each salesman starts from the same city c_l, visits different cities for only one time, and finally returns to the initial city c_l. The purpose of route planning is to take the lowest distance cost which is generated by all salesmen during the route traveling.

B. MTSP-BASED UAV-SENSOR ASSOCIATION MECHANISM

In order to find the shortest total flight distance of UAVs, we regard the data center as departure city of the traveling salesmen, regard multiple UAVs as multiple traveling salesmen and regard the sensors to be collected as other cities, thus turning the UAV-sensor association problem and collection order problem as MTSP.

It is worth noting that in the case of ensuring the shortest total distance, it is very likely that there will be a much longer route of a UAV than others, the UAV is overloaded, and a certain route is too short. It may even happen that some UAVs complete all the acquisition tasks, while others fly directly back to the data center. So we choose to import the concept of equilibrium based on the multi-traveler problem. The significance of equilibrium is to make each route as balanced as possible. To simplify the calculation, we define the equilibrium as:

$$J = \max(l_1, l_2, \ldots, l_i, \ldots, l_M), \quad i \in \mathcal{M}. \quad (12)$$

where $l_i = \sum_{j,k=1}^{N} a_{jk}^i \times d_{jk}$ represents total flight distance of UAV i, d_{jk} is distance between sensor j and sensor k. This equilibrium is defined by making the longest flight distance of UAV as short as possible and has several advantages over the traditional definition:

(1) The equilibrium defined in this paper is closer to the total distance in terms of dimension than the traditional definition, and it is relatively simple to process.

(2) In fact, as long as the longest route can be kept to a minimum, the length between the routes is small, so it also meets the definition of equilibrium.

(3) The definition is simple, which greatly reduces the amount of calculation.

In order to consider the total distance of all UAVs $S = \sum_{i=1}^{M} l_i$ and equilibrium, we first need to unify the dimension, we can get the total objective function as: ($P1$):

$$\min_{T}(aS + bJ') \quad (13a)$$

$$s.t. \sum_{i=1}^{M}\sum_{j=1}^{N} a_{jk}^i = 1, \quad \forall i \in \mathcal{M}, j \in \mathcal{N}, \quad (13b)$$

$$\sum_{i=1}^{M}\sum_{k=1}^{N} a_{jk}^i = 1, \quad \forall i \in \mathcal{M}, k \in \mathcal{N}, \quad (13c)$$

$$a_{jk}^i \in \{0, 1\}, \quad \forall i \in \mathcal{M}, j \in \mathcal{N}, \quad (13d)$$

where $J' = M \times J$, $a + b = 1$, a and b are the weights of S and J', respectively. (14) indicates that each sensor can only be served by one UAV, and (15) indicates that all sensors must be served. In order to make the total distance and the degree of equilibrium have the same effect on the overall goal, we can set the weight to 1 : 1, so we get the objective function: ($P1$):

$$\min_{A}(\frac{1}{2}S + \frac{1}{2}J') \quad (14a)$$

$$s.t. \sum_{i=1}^{M}\sum_{j=1}^{N} a_{jk}^i = 1, \quad \forall i \in \mathcal{M}, j \in \mathcal{N}, \quad (14b)$$

$$\sum_{i=1}^{M}\sum_{k=1}^{N} a_{jk}^i = 1, \quad \forall i \in \mathcal{M}, k \in \mathcal{N}, \quad (14c)$$

$$a_{jk}^i \in \{0, 1\}, \quad \forall i \in \mathcal{M}, j \in \mathcal{N}. \quad (14d)$$

The optimization problem ($P1$) is a np-hard problem which is difficult to solve. We apply genetic algorithm to solve it.

Genetic algorithm is a computational model that simulates the natural selection of biological evolution theory and the biological evolution process of genetic mechanism. It is a method to search for optimal solution by simulating natural evolution process. The specific practices are shown as algorithm 1.

Algorithm 1 Genetic Algorithm for UAV-Sensor Association Mechanism

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Input: the coordinates of data center (x_D, y_D), UAVs $(X_i(t_0), Y_i(t_0), H)$ and all sensors (x_j, y_j), where $i \in \mathcal{M}, j \in \mathcal{N}$.

Output: Best UAV-sensor association and collection sequence T^*;

1: Generate l coded individual initially
2: **for** *each timeslot t* **do**
3:   Calculate the objective function of each individual according to (14a)
4:   Use the roulette method to select N individuals as the next generation of variant objects
5:   The selected individuals are cyclically mutated according to probability, cross-selected, and generate a new generation of groups
6:   Compare selected individuals with existing records, if better than the existing records, record the group of the best l individuals
7: **end for**
8: **return** T^*

We have learned through numerous independent simulation that the utility function value after rounded is very close to the minimum value. And the method of rounding can greatly reduce the complexity of the solution.

IV. FLIGHT TIME MININIZATION OF SINGLE UAV FOR DATA COLLECTION

Since the UAV-sensor association mechanism is given in the previous section, the multi-UAV data collection flight time minimization problem can be simplified into multiple single-UAV data collection problems, so as to reduce the complexity of optimization problem. We we optimize the collection time of each UAV separately to achieve the goal of minimizing collection task completion time.

A. PROBLEM FORMULATION

In this paper, we define the task completion time as the flight time used by the UAV which flies back to the data center at the latest, and to solve this problem, we need to give the flight time of all UAVs. Note that the flight time for each UAV is independent of other UAVs, so we can give the problem formulation for single UAV. The problem formulation for single UAV can be expressed as: $(\boldsymbol{P2})$:

$$\min_{x_j^{cp}, v_{ij}, P_j(t)} \sum_{j,k=1}^{K_i} (1-s_j)(t_{jk_{fu}i} + t_{jk_{nu}i})$$

$$+ s_j(t_{jk_{hu}i} + t_{jk_{nu}i}) \tag{15a}$$

$$s.t. \ (7) \ and \ (8), \quad \forall j \in N, \tag{15b}$$

$$p_{uj}(t) \geq 0, \quad \forall j \in N, \tag{15c}$$

$$0 \leq x_j \leq d_j, \tag{15d}$$

$$0 \leq v_{ij} \leq v_{\max}, \quad \forall j \in N. \tag{15e}$$

The problem above includes variables to be optimized which are sensor transmit power $P_j(t)$, UAV's speed v_{ij} and horizontal distance between CP and sensor j x_j^{cp}.

It can be seen for this problem to obtain the position optimal collection position (OCP) for all sensors is difficult when they collect data during flying since the OCPs are determined by the collection order of sensors. But note that the OCP of one sensor is independent of the others, so the key to solve this problem is find the OCP of each sensor. According to the OCP, we can obtain the minimum flight time between two sensors and the problem to minimize flight time of UAV convert to a shortest path planning problem. Since we assume the UAV can collect data when flying or hovering and the two modes have different solution, we need to discuss them separately.

Since UAV always flies from one sensor to another sensor which means the solution for single sensor can be extended to multiple sensors, and strategy of multiple sensors data collection can be done in two steps. Firstly, opyimize collection sensor transmit power $P_j(t)$, UAV's speed v_{ij} and horizontal distance between CP and sensor j x_j^{cp} of flying mode and hovering mode, respectively, and then determine the better collection mode of each sensor.

B. FLIGHT TIME MINIMIZATION OF SINGLE UAV ON FLYING MODE FOR DATA COLLECTION

When UAV chooses flying mode, the OCP need to be determined and to find OCP of all sensors, we give the solution of single sensor at first. UAV i flies from a position to collect data of sensor j, problem formulation of this scenario can be expressed as

$(\boldsymbol{P2-a})$:

$$\min_{x_j^{cp}, v_{ij}, P_j(t)} (t_{jk_{fu}i} + t_{jk_{nu}i}) \tag{16a}$$

$$s.t. \quad (11e), (11f), (11g) \ and \ (11h). \tag{16b}$$

Clearly, the problem above includes variables to be optimized which are sensor transmit power $P_j(t)$, UAV's speed v_{ij} and horizontal distance between CP and sensor j x_j^{cp}, and these subproblems can be solved separately.

1) POWER ALLOCATION

Assume that optimal speed v_{ij}^{op} of UAV i and horizontal distance between optimal collection position and sensor j x_j^{ocp} are known, then minimum flight time can be obtained if sensor j allocates its power to maximize throughput [16]. The problem can be expressed as

$$\max_{P_j(t) \geq 0} \int_0^{\frac{x_j^{ocp}}{v_{ij}^{op}}} \frac{W}{M} \log_2(1 + \gamma_{ij}(t)) dt \tag{17a}$$

$$s.t. \int_0^{\frac{x_j^{ocp}}{v_{ij}^{op}}} P_j(\tau) d\tau \leq E_j. \tag{17b}$$

Let $s = x_j^{ocp} - v_{ij}^{op}t$, (6) can also be written as $d_{ij}(s) = \sqrt{s^2 + H^2}$, then problem (14) above can be rewritten by

$$\max_{P_j(s) \geq 0} \frac{W}{Mv_{ij}^{op}} \int_0^{x_j^{ocp}} \log_2(1 + \gamma_{ij}(s))ds \quad (18a)$$

$$s.t. \quad \frac{1}{v_{ij}^{op}} \int_0^{x_j^{ocp}} P_j(s)ds \leq E_j. \quad (18b)$$

It is worth noting that we can obtain optimal upload throughput if constraint (18b) is satisfied with equality. Moreover, longer distance means worse channel condition, so we use water filling method allocating power to maximize resource utilization. We solve the problem by Lagrangian function which can be written as

$$L = \frac{W}{Mv_{ij}^{op}} \int_0^{x_j^{ocp}} \log_2(1 + \gamma_{ij}(s))ds$$
$$- \lambda(\frac{1}{v_{ij}^{op}} \int_0^{x_j^{ocp}} P_j(s)ds - E_j), \quad (19)$$

by setting $\frac{\partial L}{\partial P_j(s)} = 0$, the optimal power allocation can be expressed as

$$P_j^*(s) = \frac{1}{\xi_0} - \frac{1}{\xi(s)}, \quad (20)$$

where $\xi_0 = \frac{1}{\lambda}$ denotes the water level, $\xi(s) = \frac{1}{\sigma^2 L_{dB}(s)}$ is channel gain. Moreover, according to (18b), we can obtain

$$\frac{1}{\xi_0} \leq \frac{E_j v_{ij}^{op} + \int_0^{x_j^{ocp}} \frac{1}{\xi(s)}ds}{x_j^{ocp}}. \quad (21)$$

Optimal upload throughput can be find if (21) satisfies with equality, so expression of maximum upload throughput can be obtained

$$B_{\max}(x_j^{ocp}, v_{ij}^{op}) = \frac{W}{Mv_{ij}^{op}} \int_0^{x_j^{ocp}} \log_2(\frac{\xi(s)}{\xi_0})ds. \quad (22)$$

2) THE OPTIMIZATION OF UAV's SPEED

Since $P_j(s) \geq 0$, the constraint $\frac{1}{\xi_0} \geq \frac{1}{\xi(s)}$ must be satisfied. By exploiting the expression of $\frac{1}{\xi(s)}$, we can find it monotonically increasing with $0 \leq s \leq x_j^{ocp}$, so the following expression is true,

$$\frac{1}{\xi_0} \geq \sigma^2 L_{dB}(x_j^{ocp}). \quad (23)$$

Based on (23), the speed v_{ij} can be given by

$$v_{ij} \geq \frac{x_j^{ocp}\sigma^2 L_{dB}(x_j^{ocp})}{E_j} - \frac{\sigma^2}{E_j}\int_0^{x_j^{ocp}} L_{dB}(s)ds. \quad (24)$$

Denote the minimum speed $v_{\min}(x_j^{ocp})$ to satisfy sensor's power constraint as

$$v_{\min}(x_j^{ocp}) = \frac{x_j^{ocp}\sigma^2 L_{dB}(x_j^{ocp})}{E_j} - \frac{\sigma^2}{E_j}\int_0^{x_j^{ocp}} L_{dB}(s)ds. \quad (25)$$

To minimize the flight time of UAV, speed of UAV should be as large as possible and to find optimal speed v_{ij}^{op}, we give following result.

Theorem 1: The maximum throughput $B_{\max}(d_j^{ocp}, v_{ij})$ is a decreasing function of v_{ij}.

Theorem 1 has been proved in [16]. Then the optimization over v_{ij} following with the given power allocation and x_j^{ocp} can be expressed as

$$\min_{v_{ij}} (\frac{x_{ij}^{ocp}}{v_{\max}} + \frac{x_j^{ocp}}{v_{ij}}) \quad (26a)$$

$$s.t. \quad B_{\max}(x_j^{ocp}, v_{ij}) \geq B_j, \quad (26b)$$

$$v_{\min}(x_j^{ocp}) \leq v_{ij} \leq v_{\max}. \quad (26c)$$

To tackle the problem (26), we need to check the feasibility of (26b), under the premise of satisfying constraint (26b), optimal speed v_{ij}^{op} can be find by binary search algorithm depending on Theorem 1.

3) THE OPTIMIZATION OF COLLECTION POSITION

With optimal power allocation and v_{ij}^{op}, the optimization over d_j^{cp} can be given by

$$\min_{x_j^{cp}} (\frac{x_{ij}^{cp}}{v_{\max}} + \frac{x_j^{cp}}{v_{ij}^{op}(x_j^{cp})}) \quad (27a)$$

$$s.t. \quad 0 \leq x_j^{cp} \leq x_{ij}. \quad (27b)$$

This problem can be solved by one-dimensional line search since $v_{ij}^{op}(x_j^{cp})$ is only relate to x_j^{cp}. By sampling n point in range $[0, x_{ij}]$ with identical inter-point distance, x_j^{ocp} can be found in the n search point and complexity of the algorithm is $O(n)$.

C. FLIGHT TIME MINIMIZATION OF SINGLE UAV ON HOVERING MODE FOR DATA COLLECTION

It is worth noting that when only using flying mode, there is a possibility that the collection task can not be completed, since the little energy of sensors can not support transmission of a large amount of data using water-filling method. Collecting data on flying mode, distance between UAV and sensor is farther than hovering mode which makes channel conditions worse, that is, the transmission of the same amount of data requires more power. In other words, when flying mode cannot complete collection task, we need to use hovering mode for data collection. For hovering mode, we consider the problem of determining minimizing flight time of single UAV by optimizing sensor transmit power since UAV's speed $v_{ij} = v_{\max}$ and horizontal distance between CP and sensor j $x_j^{cp} = 0$, which can be written as

$(P2 - b)$:

$$\min_{P_j} (t_{jk_{hu}i} + t_{jk_{nu}i}) \quad (28a)$$

$$s.t. \quad (9), (10) and (11f), \quad \forall i \in \mathcal{M}, \quad \forall j \in \mathcal{K}_i, \quad (28b)$$

To solve problem (28), we give following theorem at first.

TABLE 2. Simulation parameters.

Notation	Definition	Value
H	the altitude of UAV	$50m$
σ^2	the noise power	$-110dBm$
f_c	the carrier frequency	$2GHz$
c	the speed of light	$3 \times 10^8 m/s$
α_0	pathloss exponent	2
B	bandwidth	$1MHz$
μ_{LoS}	Additional pathloss to free space for LoS	$3dB$
μ_{NLoS}	Additional pathloss to free space for LoS	$23dB$
ψ	constant value	11.95
β	constant value	0.14
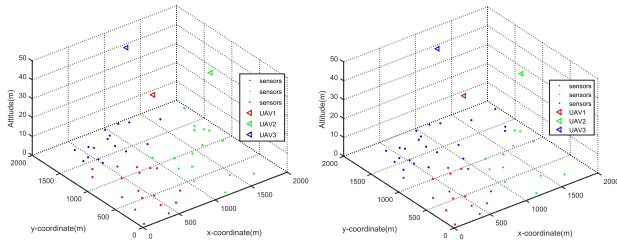
(a) Proposed optimal UAV-sensor association mechanism (b) Mechanism which only considers the total flight distance of all UAVs

FIGURE 3. UAV-sensor association given the locations of UAVs.

Theorem 2: *The left side of (10) is increasing with respect to T_j.*

Proof: The constraint (10) can be expressed as $f(x) = ax\log_2(1 + \frac{b}{x})$, $a > 0$, $b > 0$. Note that

$$f''(x) = \frac{-ab^2}{\ln 2 \times x(b+x)^2} < 0,$$

so $f'(x) = a\log_2(1 + \frac{b}{x}) - \frac{ab}{(\ln 2)\times(b+x)} \geq f'(+\infty) = 0$.

Therefore, $f(x)$ is increasing and Theorem 2 is true. □

According to Theorem 2, the minimum flight time T_j can be obtained by using binary search algorithm if (10) is satisfied with equality.

V. EVALUATION

In this section, we use Matlab software as a simulation platform to verify performance of the proposed multi-UAV collaborative data collection mechanism. Considering a geographical area of size 2 km × 2 km. Assume the position of sensors and the initial position of UAVs are randomly distributed in the geographical area. Sensors' information bits and energy are given in the range of $[0.5 \times 10^7 \text{ bits}, 4 \times 10^7 \text{ bits}]$ and $[0.25 J, 2.25 J]$, respectively. Other parameters are listed in Tabel 2. Fig. 2 and fig. 3 show the results of partitioning and path planning, respectively.

Fig. 2 shows the proposed optimal UAV-sensor association method and the UAV-sensor association only considers total flight distance of all UAVs. In this case, we consider 3 UAVs and 50 wireless sensors. We can see that UAV 3 in Fig. 2 has a lot more sensors than other UAVs. Therefore UAV 3 can't serve sensors fairly. In the proposed UAV-sensor association
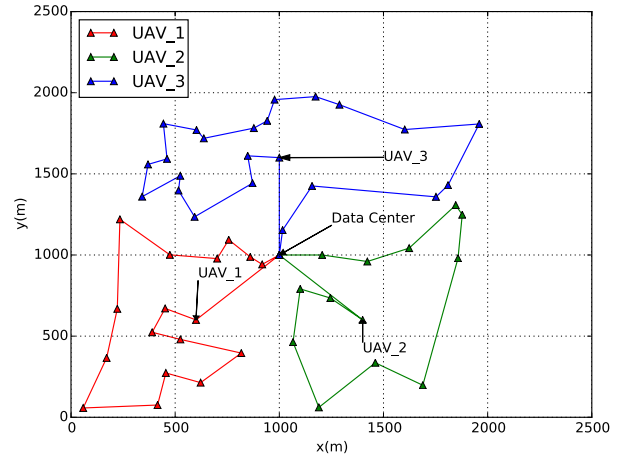

FIGURE 4. The trajectory of multi-UAVs collaborative data collection system, where $M = 3$ and $N = 50$.
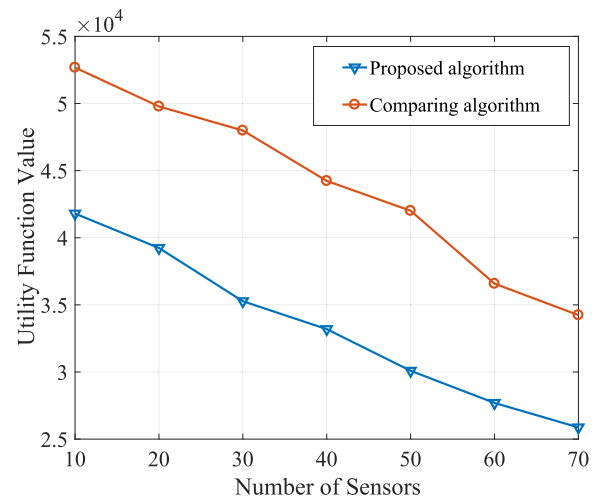

FIGURE 5. Utility function value as a function of the number of UAVs.

mechanism, the number of users served by UAV 3 is reduced, that is, the proposed UAV-sensor association mechanism is more fair than the mechanism which only considers the total flight distance of all UAVs. Fig. 3 shows the process of three UAVs flying back to the data center after starting from the data center and completing the data collection task according to the track shown in the figure. It can be seen that the distance of each UAV is close and the total distance is short.

Fig. 4 shows the utility function value (for 3 UAVs) when the number of sensors changes. The utility function of this paper considers both the overall flight distance of system and the individual fairness. Obviously, our UAV-sensor association mechanism is superior to the mechanism which only considers the total flight distance of all UAVs. In addition, as the number of UAVs increases, the total throughput of the ground sensors increases. It can also be concluded that more UAVs bring higher efficiency.

Fig. 5 shows the average number of sensors in each cell partition where the number of UAVs is set to 5. In the baseline case, the average number of sensors per cell significantly
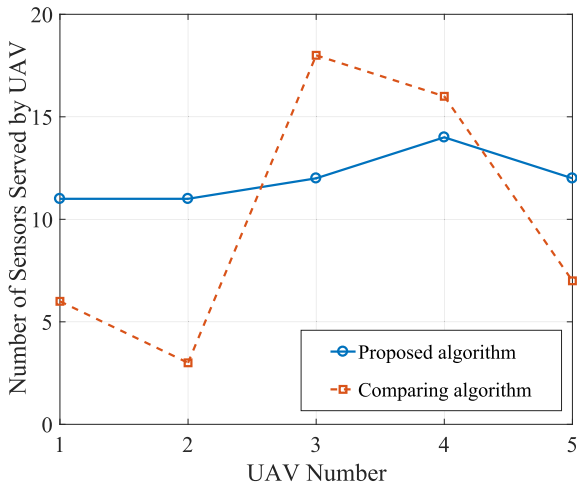
FIGURE 6. Average number of sensors per cell partition.

FIGURE 7. Collection task completion time versus average amount of data.

FIGURE 8. Collection task completion time versus average amount of energy.

varies for different cell partitions. For instance, the average number of sensors served by UAV 3 is 6 times higher than UAV 2. Consequently, in the proposed approach, the cell partitions contains an equal number of sensors. Therefore, our approach avoids generating unbalanced cell partitions and, hence, it leads to a higher level of fairness.

We further evaluate the average performance with random data requirement, random energy and random locations. The amount of data in each sensor follows uniform distribution with a mean value B_n, the amount of energy in each sensor follows uniform distribution with a mean value E_n. The results are illustrated in Figs. 6 and 7.

It can be seen in Fig. 6 that when the average amount of energy is sufficient, the average flight time grows almost linearly with the increase of B_n. But when the amount of energy is deficient (e.g., $E_n = 0.75$ J), the average flight time grows exponentially with the increase of B_n. This is due to the different relations between the flight time and the amount of data in hovering mode and flying mode. In energy sufficient case, the UAV collects data mainly in flying mode. While in energy constrained case, it collects data mainly in hovering mode.

In Fig. 7, it is observed that when the amount of data is small, the average flight time is constant over all examined values of E_n, which means that the UAV can fly with the maximum speed and collect data during flying. In addition, it is expected with the increase of E_n, the curves converges to a fixed point with minimum flight time, i.e., the UAV flies with the maximum speed. However, the figure shows that the convergence is slow, especially for large values of B_n. For the case with $B_n = 1$ Mb, the curve firstly goes down exponentially, and then linearly with close-to-zero slope.

In Fig. 8, we plot completion time of data collection against the number of sensors in the scenario, where the number of UAV is set to 3. Completion time is 0 to denote a unfinished collection task. As shown in Fig. 8, we can find that the proposed fly_hover data collection mode always outperforms
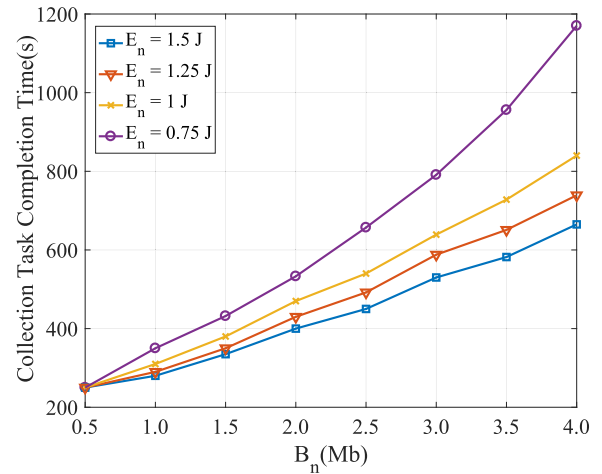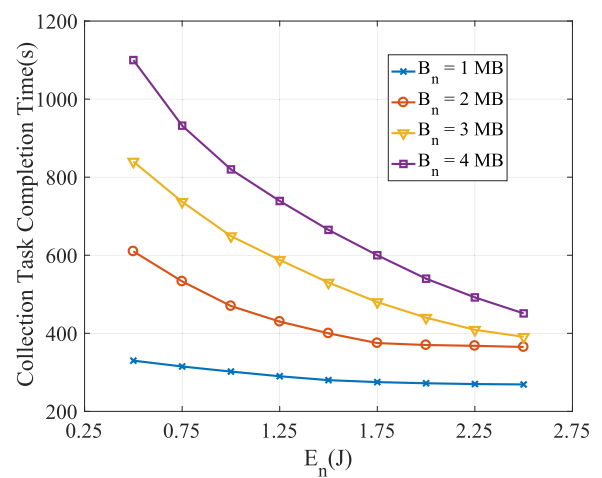
hovering only mode and flying only mode. This is because our proposed data collection strategy can choose flying mode and hovering mode based on energy of sensors and amount of data to be uploaded, avoiding the situation that the data collection task cannot be completed. Meanwhile, the proposed strategy also optimizes CP and speed of the UAV as well as the transmit power of sensors according to the data collection mode.

Furthermore, the completion time of data collection against the number of UAVs is shown in Fig. 9, where the number of sensors is set to 50. Obviously, using more UAVs can reduce task completion time and the proposed fly_hover joint collection strategy always obtains the shortest completion time compared with other strategies. Clearly, as the number of UAVs increases, the collection task completion time can be greatly decreased, which effectively improve the data collection efficiency. However, as the number of UAVs further increases, the completion time of collection task reduces slowly and stabilizes.
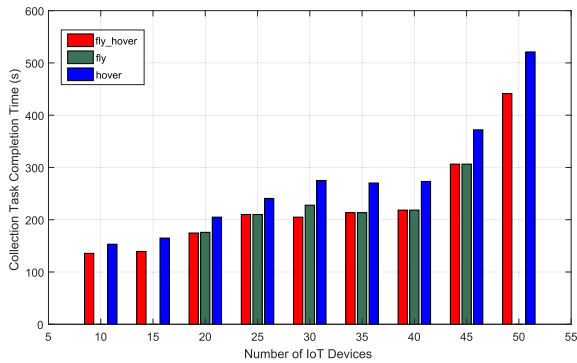
FIGURE 9. Collection task completion time versus the number of sensors for $M = 3$.
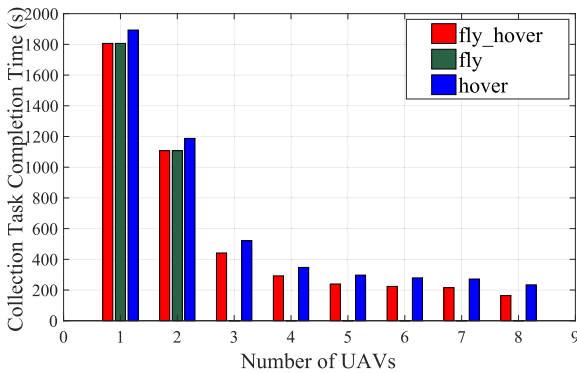

FIGURE 10. Collection task completion time versus the number of UAVs for $N = 50$.

VI. CONCLUSION

This paper solves the problem of minimizing flight time required to complete multi-UAV data collection task in a two-dimensional sensor network. Firstly, we propose a load-balanced UAV sensor correlation mechanism that can improve system throughput. The complex multi-UAV data collection problem is simplified to multiple single UAV data collection problems. Through the analysis of single sensor conditions, The optimal solution structure is obtained by collection mode, UAV-user association scheme and collection sequence, sensor power, flight speed and collection position optimization. Finally, the single sensor problem was extended to the multi-sensor problem with a similar traveling salesman problem. The numerical results show that the UAV-sensor association scheme improves the overall fairness of the system, and the multi-UAV data collection scheme shortens the task completion time. In future work, we will consider the Droppler effect caused by UAV moving. Also, channel fading and wireless sensors' mobility will be conducted as part of a future work.

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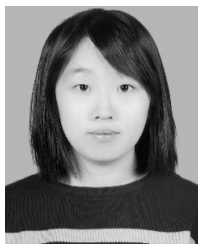
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