Aerial Data Collection with Coordinated UAV and Truck Route Planning in Wireless Sensor Network

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***Abstract*—Unmanned aerial vehicle (UAV) is a promising way to collect data generated by wireless sensor networks, nevertheless, the battery capacity of the UAV restricts its application on many occasions, e.g., the network deployed in the wild. In this paper, we propose a coordinated route planning scheme to deal with the energy issue of the UAV, where a truck carrying backup batteries moves together with the UAV as a "mobile recharging station". Our optimization task is to minimize the total mission time for collecting data from all the sensor nodes. We develop an efficient clustering algorithm to divide the entire mission area into multiple subregions in a load-balanced way to minimize the number of movements of the UAV, and formulate the trajectory planning task as a coordinated traveling salesman problem which is heuristically solved by a three-step route planning algorithm. Numerical results show that our proposed scheme provides an effective and cost-efficient way for the data collection of wireless sensor networks in practical application scenarios.**

***Index Terms*—Data collection, trajectory planning, unmanned aerial vehicles, wireless sensor network.**

I. Introduction

Wireless sensor network (WSN), consisting of numerous spatially distributed and dedicated sensor nodes (SNs) for monitoring and recording ambient environment conditions, is recognized as an indispensable component of the Internet of Things [1]. WSNs have profound effects on both military and civil applications, including intrusion detection, homeland security surveillance, precision agriculture, forest fire inspection, animal tracking, etc. [2] The data collection of the SNs is a major issue in WSNs, and the related works can be roughly categorized into three types according to the transmission approaches for data gathering from SNs to the data center, i.e., static sink, ground mobile sink and aerial mobile sink. Traditionally, the data of SNs is collected via a multi-hop routing network to the ground base station in a static manner, the key point of this type is on the routing design to find optimal forwarding routes [3]. Whereas, collecting a massive amount of data from widely deployed SNs would cause excessive use of the relay nodes and unreliable wireless links, which lead to reduced network lifetime and low data transmission rates, respectively. Mobile sinks are introduced to overcome these problems, in which one or more ground vehicles equipped with data sinks are employed for data collection. Since the routing network is partially or fully replaced by the ground mobile sinks, this approach can alleviate the burden of SNs for relay [4]. However, it is noteworthy that the intrinsic defect of the aforementioned WSN application scenarios is that the SNs are usually deployed in the vast land, which means that the deployment of supporting infrastructures is difficult and expensive in these remote areas such as the wilderness. In addition, some areas are dangerous and unreachable (e.g., over the water) for ground vehicles, increasing the difficulty for data collection.

Recently, with the breakthroughs in design and production, unmanned aerial vehicles (UAVs) have attracted significant attention in many domains [5]–[7]. Due to the high flexibility and mobility, the UAVs can act as aerial mobile sinks to enable fast and reliable data collection in WSNs. The UAVs can fly towards clusters of SNs and provide low power communication [8], which is more efficient compared to low-speed and road-restricted ground mobile sinks. Moreover, UAVs can also leverage the line-of-sight dominated air-to-ground channels to enhance the quality of data transmission [9]. In [10], a comprehensive UAV-aided data collection framework for large-scale WSNs is proposed, where the data gathering mission is modeled as a traveling salesman problem (TSP) and solved by a fast path planning algorithm for the case considering the evenly-deployed SNs. Given a one-dimensional WSN and one UAV, [11] optimizes the time-varying UAV speed as well as the transmission interval to minimize the total data collection time. In [12], the UAV's trajectory is optimized along with the wake-up mechanism of SNs to achieve energy-saving for SNs while guaranteeing reliable data collection in fading channels. Considering the SNs with different and limited buffer sizes, a time-sensitive data collection mission to maximize the total number of served SNs is studied in [13], where the UAV's trajectory and radio resource allocation are jointly optimized via a successive convex approximation algorithm.

Nevertheless, the on-board battery capacity tends to be a fatal limitation that greatly influences the performance of the UAV. Recent works envisage that the battery of the UAV can be recharged or replaced whenever used up during its tour, which can be enabled by an automatic battery replacement system. In [14], the throughput-oriented scenario with one fixed charging station and multiple rechargeable UAVs is studied. The node assignment and UAVs' trajectory are jointly designed to provide seamless coverage for ground SNs while only three nodes are considered in this work. In [15], the

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region of interest is divided into multiple grids, where wireless charging devices for the UAV are placed at the center of each grid. Reinforcement learning is introduced to make the decisions of selecting the charging point, the flying height and the connected SN so as to improve the energy-efficiency of the UAV. Optimal deployment of UAV charging stations is investigated in [16], where the flying distance of the UAV as well as the number of charging stations is minimized. However, the scalability and flexibility are limited since the deployment of charging stations is fixed.

Fundamentally speaking, the energy issue is still a bottleneck of the UAV-aided data collection systems in real application scenarios. In this paper, we investigate a promising mobile sink approach to realize high-efficient periodic data collection for large-scale WSNs deployed in the suburban, where a UAV is dispatched to hover above the clusters of SNs to receive data and a truck carrying backup batteries moves together with the UAV to compensate for the shortage of UAV energy. We aim to minimize the mission time for collecting data from all the SNs with the battery constraint of the UAV. First, a clustering method is introduced to divide the mission region into multiple subregions with an approximately equal number of SNs in each subregion based on the maximal coverage radius and capacity of the UAV, where the horizontal and vertical positions of the UAV are determined by the cluster center and the subregion size, respectively. Second, we show that the trajectory design issue can be modeled as a modified TSP to find the sequence of visiting target subregions as well as the locations that the UAV and the truck meet each other. To our best knowledge, this is the first work that studies the UAV-enabled data collection in WSNs with a "mobile recharging station" from a coordinated route planning perspective. Finally, we develop efficient algorithms to solve the optimization task. Numerical results verify that our proposal is effective and efficient, which can provide a guideline for the system design of data collection in practice.

The rest of the paper is organized as follows. Section II introduces the data collection model as well as the formulation of the optimization task. In Section III, our proposed algorithm is given in detail. Section IV provides numerical results and performance evaluation, followed by conclusions in Section V.

II. System Model And Problem Formulation

A. Network Description

As depicted in Fig. 1, we consider a WSN located in region $\mathcal{R} \in \mathbb{R}^2$, consisting of one data center, one truck, one rotary-wing UAV and M SNs. The set of SNs is denoted by $\mathcal{S} = \{s_1, s_2, ..., s_M\}$, where the location of SN $s_k \in \mathcal{S}$ is $\boldsymbol{z}_k = (s_k^x, s_k^y, 0)$. The UAV operates in hovering to collect the data from ground SNs, thus the region is divided into N subregions so that the UAV can collect data from SNs in each subregion through one taking-off and landing. The set of subregions and UAV's 3D hovering positions are represented by $\mathcal{R}_s = \{R_1, R_2, ..., R_N\}$ and $\mathcal{H} = \{\boldsymbol{h}_i, 1 \leq i \leq N\}$, respectively. The hovering time for data collection is set as T_h, which is fixed for each lifting-off with the consideration

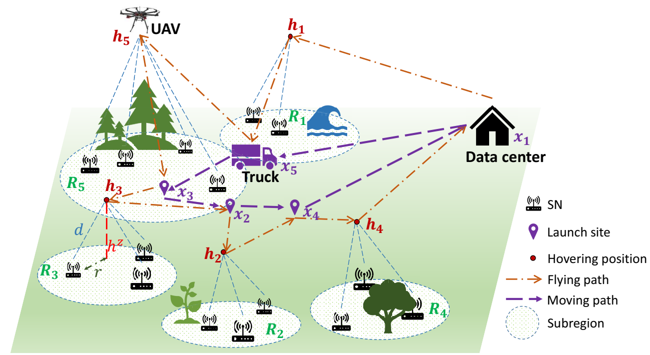

Fig. 1. Data collection of WSN in suburban environment.

of the battery capacity of the UAV. When the UAV hovers at $\boldsymbol{h}_i = (h_i^x, h_i^y, h_i^z)$, it establishes communication links with the SNs in subregion R_i and collects data from them. The UAV needs to fly back to the truck for battery replacement before visiting the next subregion, the locations at which they rendezvous with each other is denoted by "launch site" $\mathcal{X} = \{\boldsymbol{x}_i = (x_i^x, x_i^y, 0), 1 \leq i \leq N\}$. Let $U_N \ni \sigma(\cdot)$ denote the set of permutations of $\{1, 2, ..., N\}$ representing all the possible sequences of visiting subregions, where we set $\sigma(N+1) = \sigma(1)$ to simplify the notation (e.g., $\sigma = \{1, 5, 3, 2, 4, 1\}$ in Fig. 1). Then, the whole trajectories of the truck and the UAV can be represented as $[\boldsymbol{x}_{\sigma(1)}, \boldsymbol{x}_{\sigma(2)}, ..., \boldsymbol{x}_{\sigma(N+1)}]$ and $[\boldsymbol{x}_{\sigma(1)}, \boldsymbol{h}_{\sigma(1)}, \boldsymbol{x}_{\sigma(2)}, ..., \boldsymbol{h}_{\sigma(N)}, \boldsymbol{x}_{\sigma(N+1)}]$, respectively.

B. Channel Model

Different from the ground-to-ground channel, the air-to-ground channel takes both line-of-sight (LoS) links and non-line-of-sight (NLoS) links into consideration. The probability of LoS is influenced by the position of the UAV and SNs, geographic environments, density and height of buildings and so on, which can be closely approximated to a simple modified sigmoid function of the following form [9]:

$$P_{LoS}(\phi) = \frac{1}{1 + a\exp[-b(\phi - a)]}, \tag{1}$$

where a, b are parameters that rely on the environment, ϕ is the elevation angle between the SNs and UAV, which is calculated as $\phi = \frac{180^\circ}{\pi}\arctan(h^z/r)$, where h^z is the altitude of the UAV and r is the ground distance between the SNs and UAV, which is illustrated in Fig. 1.

The air-to-ground mean path loss model can be expressed as follows:

$$\begin{aligned} L_{LoS} &= L_{FSPL} + \eta_{LoS}, \\ L_{NLoS} &= L_{FSPL} + \eta_{NLoS}, \end{aligned} \tag{2}$$

where L_{FSPL} represents the free space path loss between the UAV and ground receivers, η_{LoS} and η_{NLoS} refer to the mean value of the excessive path loss of LoS and NLoS links, respectively. Also note that the probability of NLoS links is

$P_{NLoS}(\phi) = 1 - P_{LoS}(\phi)$, so the average path loss model can be expressed as follows [17]:

$$\begin{aligned} L(h^z, r) &= P_{LoS}(\phi) * L_{LoS} + P_{NLoS}(\phi) * L_{NLoS} \\ &= 20\log d + 20\log f_c + 20\log\left(\frac{4\pi}{c}\right) + P_{LoS}(\phi)\eta_{LoS} \\ &\quad + \big(1 - P_{LoS}(\phi)\big)\eta_{NLoS} \\ &= 20log\sqrt{(h^z)^2 + r^2} + \frac{A}{1 + a\exp\big[-b\big(\arctan(\frac{h^z}{r}) - a\big)\big]} + B, \end{aligned} \tag{3}$$

where c is the speed of light, f_c represents the carrier frequency. $A = \eta_{LoS} - \eta_{NLoS}$ and $B = 20\log f_c + 20\log(\frac{4\pi}{c}) + \eta_{NLoS}$ are constants under a given environment.

To guarantee the data transmission between the UAV and SNs, a threshold Υ is introduced to represent the maximum allowable path loss corresponding to the minimum transmission rate requirement of data collection. SNs are supposed to be able to connect to the UAV if $L(h^z, r) \leq \Upsilon$, i.e., the maximum coverage radius can be mathematically expressed as $r_{max} = \{r | L(h^z, r) = \Upsilon\}$. Fig. 2 shows the variation of r with respect of h^z as per (3) for the suburban environment, where Υ is set as 110dB. The coverage radius rises first and then decreases as the altitude of the UAV increases, this suggests that the altitude of the UAV could be adjusted while satisfying the same path loss requirement. It can be calculated by $\partial r_{max}/\partial h^z = 0$ that the maximum coverage radius under this scenario is $r_{max} = 3444$ meters, which gives a reference to the number of subregions that need to be divided.

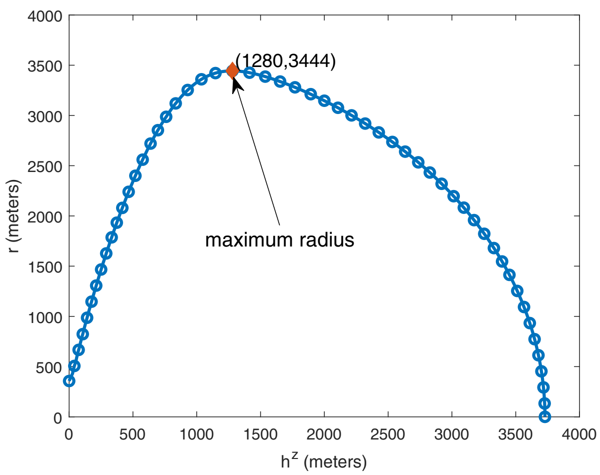

Fig. 2. Coverage radius r vs. UAV altitude h^z curve with $\Upsilon = 110$ dB, in a suburban environment.

C. Problem Formulation

We focus on the total time for all the data collection since the mission is delay-tolerant. Let $v_0, v_1 > 0$ denote the speed of the truck and the UAV, respectively, with $v_0 < v_1$. The key point of our optimization task is to find the optimal locations of launch sites, which can be mathematically formulated as follows:

$$\begin{aligned} \underset{\boldsymbol{x}_1,\ldots,\boldsymbol{x}_N,\sigma\in U_N}{\text{minimize}} \quad & \sum_{i=1}^{N} \max\Big\{\frac{1}{v_0}||\boldsymbol{x}_{\sigma(i)} - \boldsymbol{x}_{\sigma(i+1)}||, \\ & \frac{1}{v_1}\left(||\boldsymbol{x}_{\sigma(i)} - \boldsymbol{h}_{\sigma(i)}|| + ||\boldsymbol{h}_{\sigma(i)} - \boldsymbol{x}_{\sigma(i+1)}||\right) + T_h\Big\} \\ \text{s.t.} \quad & \frac{1}{v_1}E_f\left(||\boldsymbol{x}_{\sigma(i)} - \boldsymbol{h}_{\sigma(i)}|| + ||\boldsymbol{h}_{\sigma(i)} - \boldsymbol{x}_{\sigma(i+1)}||\right) \\ & + E_h T_h \leq E_{max}, \end{aligned} \tag{4}$$

where E_f, E_h are the energy consumption of flying and hovering, respectively, and the total capacity of the battery is denoted as E_{max}. The first term in $\max\{\cdot,\cdot\}$ represents the time for the truck to move from one launch site to the next, the second term corresponds to the amount of time for the UAV to leave one launch site, reach its hovering position and collect data from SNs, then return to rendezvous with the truck at the next launch site for replacing battery. The constraint guarantees that the UAV is able to return to the truck. Problem (4) is NP-hard since it is an extension of the Euclidean TSP that requires considering the positions of launch sites and battery life of the UAV.

III. Our Proposed Algorithm

To address the optimization task (4), the selection of hovering positions $\mathcal{H}$ needs to be determined at first, which can be expressed as follows: How can we divide the entire region with unevenly distributed SNs into minimal number of subregions under the constraint of UAV's capacity and maximal coverage radius? After selecting the optimal hovering positions, we propose an efficient three-step route planning algorithm to solve the trajectory optimization problem.

A. Selection of Hovering Positions

First of all, we estimate the number of subregions to be divided on the premise of satisfying the capacity and coverage constraints, which is given by:

$$N = \max\left\{\left\lceil\frac{M}{m_s}\right\rceil, \left\lceil\frac{A}{\pi r_{max}^2}\right\rceil\right\}, \tag{5}$$

where m_s is the maximum number of SNs that a UAV can serve within hovering time T_h, A is the area of region $\mathcal{R}$.

Note that, the number of subregions would be minimal when the SNs are assigned equally between the subregions. Thus, we try to divide the entire mission region into at least N subregions in a load-balanced way. Intuitively, the distribution of desired hovering positions of the UAV corresponds to the density of SNs, so $\mathcal{H}$ can be determined by normal clustering methods [18]–[20]. The SNs can gathered to a group if they are closest to the centroid of a cluster.

The flowchart of our clustering algorithm is shown in Fig. 3. I_{max}, K, θ_N, θ_d, θ_s, are the maximum number of iterations, the expected number of clusters, the minimum size of clusters, the minimum distance between two cluster centroids, the allowed standard deviation of each cluster, respectively. First,

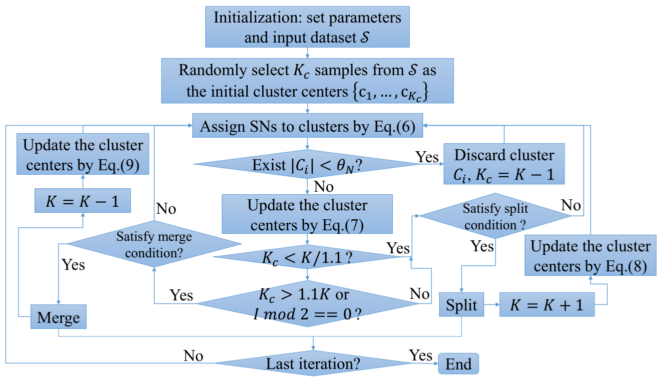

Fig. 3. The flowchart of clustering.

K_c samples are randomly selected from the input dataset as the initial centers, the corresponding clusters of which are denoted by $C_1, C_2, ..., C_{K_c}$. Then the SNs would be assigned to the cluster center closest to it, which can be mathematically expressed as:

$$C_i = \{s \in \mathcal{R} |\ ||s - c_i|| \leq ||s - c_j||,\ \forall i \neq j\}. \tag{6}$$

If the number of SNs in cluster C_i is less than θ_N, the cluster C_i would be discarded.

We explain the split and merge operations in detail. In a split procedure, the standard deviation of each cluster is calculated, and pick up the maximum denoted as ϵ_{max}. If $\epsilon_{max} > \theta_s$ and the number of SNs in this cluster is no less than $1.1\theta_N$, the split operation is triggered. In a merge procedure, the distance between all the cluster centers is calculated and denoted as matrix D_{dis}, where $D_{dis}(i,i) = 0$. If $D_{dis}(i,j) < \theta_d$, the merge operation is triggered.

The update rules of the cluster centers are as follows:

$$c_i = \frac{1}{|C_i|} \sum_{s \in C_i} s, \tag{7}$$

$$c_i^+ = c_i + \epsilon_{max},\ c_i^- = c_i - \epsilon_{max}, \tag{8}$$

$$c_{new} = \frac{1}{|C_i| + |C_j|}(|C_i|c_i + |C_j|c_j), \tag{9}$$

which correspond to the normal operation, split operation and merge operation, respectively. By split and merge, ISODATA is an effective method to find the proper clusters. We use SN set $\mathcal{S}$ as the input, and the output centroids are taken as the horizontal part of hovering positions $\mathcal{H}$.

Then, we adjust the altitude of the UAV since the cluster size (i.e., size of subregion) differs. The required coverage radius of the UAV above each subregion is $r_i = \max_k\{||(h_i^x, h_i^y, 0) - \boldsymbol{z}_k||,\ s_k \in R_i\}$, which is determined by the SNs at the border. The corresponding altitude h_i^z of the UAV above R_i can be calculated by $L(h_i^z, r_i) = \Upsilon$.

B. Optimal Route Planning

Observing the fact that the optimization problem (4) over variables $\boldsymbol{x}_i$ will be convex (a second-order cone program) if the permutation σ is fixed, we propose an efficient route planning algorithm (Algorithm 1) to solve (4), which can be concluded as the following three steps:

Step 1: Initialize the sequence of visiting all the target hovering positions $\mathcal{H}$.

We set the initial order of $\{\boldsymbol{h}_1, ..., \boldsymbol{h}_N\}$ the same as their optimal TSP tour. There are lots of methods to solve the TSP, such as ant colony algorithm, simulated annealing and so on. Lin-Kernighan heuristic (LKH) is one of the efficient methods for solving TSP, which was first proposed in [21]. Here, we employ an improved LKH solver developed in [22] to find an optimal TSP solution and initialize the visiting sequence σ.

Step 2: Solve problem (4) with fixed σ.

Given one permutation to visit all the subregions, (4) can be rewritten as follows under fixed σ:

$$\begin{aligned}
&\underset{\boldsymbol{x}_1,...,\boldsymbol{x}_{N+1},t_1,...,t_{N+1}}{\text{minimize}} \quad t_{N+1} \\
\text{s.t. } & C_1: \ t_i \geq t_{i-1} + \frac{1}{v_1}(||\boldsymbol{x}_{i-1} - \boldsymbol{h}_{i-1}|| + ||\boldsymbol{h}_{i-1} - \boldsymbol{x}_i||) \\
&\qquad + T_h,\ \forall i \in \{2, ..., N+1\}, \\
& C_2: \ t_i \geq t_{i-1} + \frac{1}{v_0}||\boldsymbol{x}_{i-1} - \boldsymbol{x}_i||,\ \forall i \in \{2, ..., N+1\}, \\
& C_3: \ ||\boldsymbol{x}_{i-1} - \boldsymbol{h}_{i-1}|| + ||\boldsymbol{h}_{i-1} - \boldsymbol{x}_i|| \\
&\qquad \leq v_1 \frac{E_{max} - E_h T_h}{E_f},\ \forall i \in \{2, ..., N+1\}, \\
& C_4: \ t_1 = 0, \\
& C_5: \ \boldsymbol{x}_1 = \boldsymbol{x}_{N+1},
\end{aligned} \tag{10}$$

where $t_{(\cdot)}$ denotes the accumulative time at each ordered point. $\boldsymbol{x}_1$ is the given location of the data center, where the UAV and truck start the tour and finally return. We can solve the this convex optimization problem by CVX, then the optimal coordinated routes under fixed ordered visiting assignment can be found.

Step 3: Explore new visiting sequences.

It is worth noting that the optimal sequence of the coordinated tour may not be the same as that induced by the TSP tour, so 2-OPT exchanges are used to explore new possible permutations, and **Step 2** is repeated under new σ for every exchange.

IV. Numerical Results

Consider a geographical region in suburban with a size of $10 \times 10\text{km}^2$, where 1000 SNs are deployed and the data center is placed at the center of the region. The suburban environment parameters for $f_c = 2$ GHz are $a = 4.88$, $b = 0.43$, $\eta_{LoS} = 0.1$, $\eta_{NLoS} = 21$, respectively [17]. The maximum allowable path loss is set as $\Upsilon = 110$ dB. The battery parameters of the UAV are $E_f = 3600$ W, $E_h = 4800$ W and $E_{max} = 600$ W, respectively. The hovering time above each region is set as $T_h = 5$ minutes with the consideration of battery capacity and correspondingly the UAV can finish data reception with 30 SNs at most during each T_h. The speeds of truck and UAV

Algorithm 1 Three-step coordinated route planning

Initialization: $\mathcal{R}$, $\mathcal{H}$, parameters of truck and UAV: $v_0, v_1, E_f, E_h, E_{max}, T_h$, and the maximum number of iteration $\mathrm{MaxIter}$.
Step 1: Using LKH algorithm to solve the TSP tour of $\mathcal{H}$ to initialize the visiting sequence;
Return the solution σ;
Step 2: Using CVX to solve (10) with σ to find the initial optimal routes;
Return $\sigma^{temp} \leftarrow \sigma$, $t_{N+1}^{temp} \leftarrow t_{N+1}$, $\boldsymbol{x}^{temp} \leftarrow \boldsymbol{x}$;
Step 3: Using 2-OPT to explore new routes:
count $= 1$;
while count $<$ MaxIter **do**
  2-OPT exchange;
  Return new σ;
  Solve problem (10) with σ;
  if $t_{N+1} < t_{N+1}^{temp}$ **then**
    $\sigma^{temp} \leftarrow \sigma$, $t_{N+1}^{temp} \leftarrow t_{N+1}$, $\boldsymbol{x}^{temp} \leftarrow \boldsymbol{x}$;
  else
    σ^{temp}, t_{N+1}^{temp}, $\boldsymbol{x}^{temp}$ do not change;
  end if
  count $\leftarrow$ count $+ 1$;
end while
return σ^{temp}, $\boldsymbol{x}^{temp}$, t_{N+1}^{temp}.

are set as $v_0 = 20$ km/h [1] and $v_1 = 80$ km/h, respectively. The time required for replacing battery can be ignored.

For preliminary preparation, the region is divided into several subregions whose load is approximately equal. As illustrated in Fig. 2, we can obtain the maximum achievable coverage radius of UAV is 3444 meters, then the estimated number of subregions that need to be divided is $N = 34$ according to (5). Thus, for the clustering method, parameters are set as $I_{max} = 100,\ K = 34,\ \theta_N = 20,\ \theta_d = 1,\ \theta_s = 1$, respectively. Fig. 4 shows the clustering result, where the squares in different colors represent the centroids of the clusters and the final number of subregions are $N = 36$. Based on the size of clusters, we adjust the altitude of the UAV to cover all the SNs in subregions. The UAV's 3D hovering positions of Fig. 4 is shown in Fig. 5.

Then, we compare our proposed scheme with two other methods: UAV-only and truck-directly. The former uses a UAV alone to fly forth and back between the data center and all the subregions, in which the data center also acts as a fixed charging station. The latter uses a truck to carry a UAV to each subregion, then the UAV flies vertically to the desired altitude for data collection and landing on the truck for battery replacement. Some evaluation indexes are employed to measure the performance. First, we denote ω as the percentage of collected subregions. Then, let D_u and D_t denote the total

[1]A relatively lower speed than normal truck speed in reality is set to compensate for the non-Euclidean distance of the truck route under real road condition, which would not influence the solution since we focus on the time to completion.

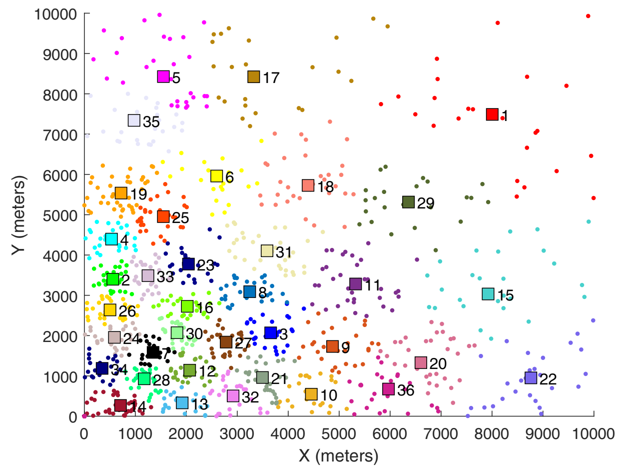

Fig. 4. Divide the region into multiple subregions in a load-balancing perspective.

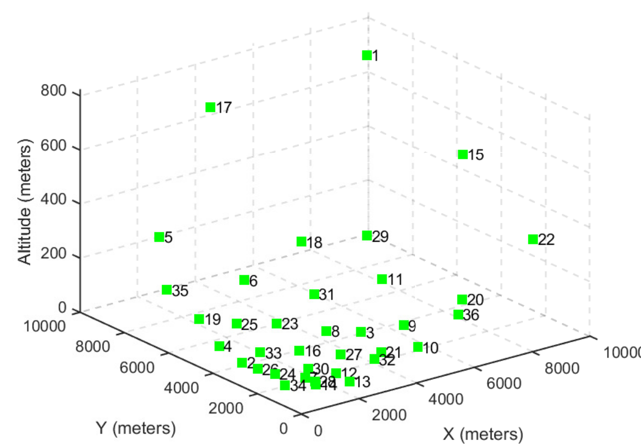

Fig. 5. The adjusted altitude of each hovering position.

traveling distance of the UAV and truck, respectively [2]. And τ is denoted as the ratio of time paid for data collection to total mission time, which indicates the efficiency of data collection. As can be seen from Table I, the UAV-only method could only

TABLE I
PERFORMANCE OF OUR PROPOSAL

Evaluation indexes	ω (%)	D_u (km)	D_t (km)	τ (%)
UAV-only	11.11	12.26	0	68.50
Truck-directly	100	18.38	49.49	34.44
Our proposal	100	87.62	38.97	73.26

serve 4 subregions of total 36 subregions due to the limited battery capacity. The UAV even can not reach the subregions in the relatively remote area, which validates the infeasibility of the method in practice. For truck-directly and our proposal,

[2]Note that D_u of truck-directly method is calculated as the distance for lifting-off and landing.

the data collection of all the SNs can be finished in 8.71 and 4.09 hours, respectively. Our proposal can save almost half of mission time since in the truck-directly method, the truck stays stationary when the UAV leaves it for data collection. As can be seen from the trajectory design result depicted in Fig. 6, the truck in our proposal takes a shorter path (38.97km) to complete the mission, this is possible because the speed of the UAV is faster than the truck's and it could catch up with the moving truck. As exploiting the agility of the UAV, the efficiency of our proposal is much higher, where 73.26% time is used on gathering data, i.e., only about 65 minutes are paid for movement, which can be considered as a high-efficient scheme. It is also worth mentioning that, the truck-directly method is greatly restricted by the deployment of SNs, the data collection mission may fail when the hovering positions, such as over the waters, are unreachable for ground vehicles.

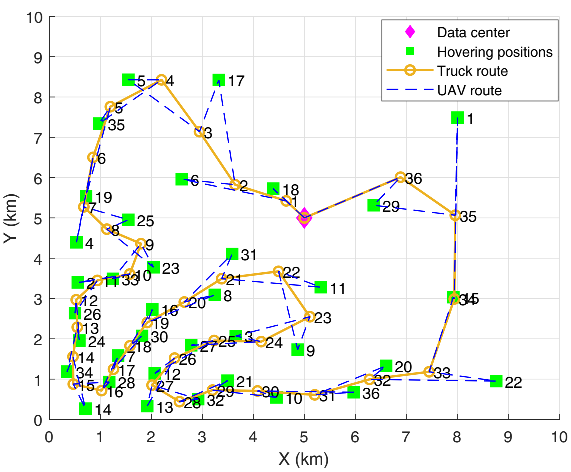

Fig. 6. Coordinated route planning result.

V. Conclusion

In this paper, we investigated the UAV-enabled data collection mission in WSNs deployed in the wild with joint consideration of data transmission and battery capacity of the UAV. We introduced a truck carrying backup batteries to move along with the UAV so that the UAV could return to the truck for battery replenishment during its flight, which not only avoids the condition that battery drains but also saves the time for flying to a fixed charging station. The task to minimize the mission time was formulated as an extension of TSP. We also proposed a novel coordinated route planning scheme to deal with the task, which can be summarized as two stages, i.e., selection of hovering positions and optimal trajectory design. First, a clustering method to divide the mission region into load-balanced subregions based on the SNs' distribution was introduced to determine the horizontal positions of the UAV, where the UAV altitudes were adjusted according to the shape of subregions. Then, we proposed a heuristic three-step algorithm to optimize the locations of launch sites so as to solve the coordinated trajectory design problem. Numerical results indicated that our proposal is the only feasible as well as high-efficient way to approach large-scale data collection in practice.

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