# Energy-Limited UAV Visiting Planning for Age-Aware Wireless-Powered Sensor Networks

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***Abstract*—Unmanned aerial vehicle (UAV) has revealed its great advantage to provide efficient data collection and wireless charging services to wireless-power sensor networks (WPSNs). Note that the UAV usually is equipped with limited battery power and therefore may not have enough energy to visit all sensor nodes (SNs) during a flight. However, the energy consumption of the UAV is rarely discussed in UAV-assisted WPSNs. In this paper, we study visiting planning problem in the UAV-assisted WPSN by considering both the energy limitation of the UAV and the age of information (AoI) of data collection. Specifically, we introduce a mixed data collection strategy to reduce the AoI of the collected data and improve the energy efficiency of the UAV during each flight. The formulated AoI-aware problem, which aims to minimize the average AoI of the collected data and meanwhile maximize the number of visiting SNs as well as the amount of data, is further tackled by utilizing the reformulation-linearization-technique (RLT) and alternating direction method of multipliers (ADMM). The results show the proposed ADMM-based algorithm can outperform other approaches in terms of system objective and energy efficiency.**

***Index Terms*—data collection, age of information, energy-limited UAV, visiting planning**

## I. Introduction

Sensor networks have been considered as a practical platform for real-time monitoring in various application scenarios, such as urban traffic, weather monitoring, and disaster warning [1]. In a sensor network, sensor nodes (SNs) are often deployed in some extreme conditions around the city for remote monitoring and it is impractical to replace their batteries frequently [2]. Fortunately, *wireless charging*, which is a promising power transfer technology to charge rechargeable SNs in different ranges, could be utilized to extend the service life of the overall sensor networks. Currently, the unmanned aerial vehicle (UAV) is becoming an indispensable part of the *wireless-powered sensor networks (WPSNs)* to not only facilitates data collection but also wirelessly charge those SNs with low power [3], [4].

To have a comprehensive and fresh overview of a remote monitoring application, it is necessary for a UAV to visit more SNs and collect more sensing data during each flight. A deep reinforcement learning (DRL)-based technique [5] is designed to find the optimal trajectory and data collection in a specific coverage area. The results in [6] show that the data transfer and energy transfer problem could be formulated as a Markov decision process (MDP) model and further optimized based on DRL schemes. A multi-objective deep deterministic policy gradient (DDPG) algorithm [7] is proposed to jointly maximize the sum data rate and total harvested energy and meanwhile minimize the UAV's energy consumption.

The *age of information (AoI)* has been proposed as a key performance metric to measure the freshness of the collected data [8], that is, the smaller AoI, the higher data freshness. Recently there has been an increasing focus on the average AoI minimization problem. The UAV's trajectory and the time required at each SN are considered in [9] to minimize the average AoI of the collected data. A deep Q-network (DQN)-based scheme [10] is proposed to minimize the average AoI by jointly optimizing the trajectory of the UAV, the scheduling of information transmission, and energy harvesting of ground nodes. A DQN-based approach was developed in [11], where the UAV trajectory design problem is formulated as MDP, and the realization goal is to minimize the accumulated AoI within a given duration.

As we know that the UAV requires a large amount of energy consumption for flying or hovering. The UAV also needs to consume some energy for data collection as well as wireless charging in the UAV-assisted WPSNs. However, the energy consumption of the UAV is rarely studied in most of research works [12], [13], which is impractical in the real world. That is, the UAV equipped with *limited battery power* may not have enough energy to visit all SNs during a flight, which causes the failure of those existing visiting planning approaches. Therefore, in the UAV-assisted WPSNs, how to minimize the average AoI and meanwhile maximize the number of visiting SNs by considering the energy consumption of the UAV has become an interesting research topic.

In this paper, we present an AoI-aware wireless-power sensor network and optimize the visiting planning of the energy-limited UAV. In the proposed WPSN, we assume that a UAV departs from the depot to execute data collection and wireless charging tasks by interacting with multiple SNs around the map. Due to the energy limitation and AoI minimization target, the UAV will finally fly back to the depot for data aggregation and battery recharging. Specifically, we introduce

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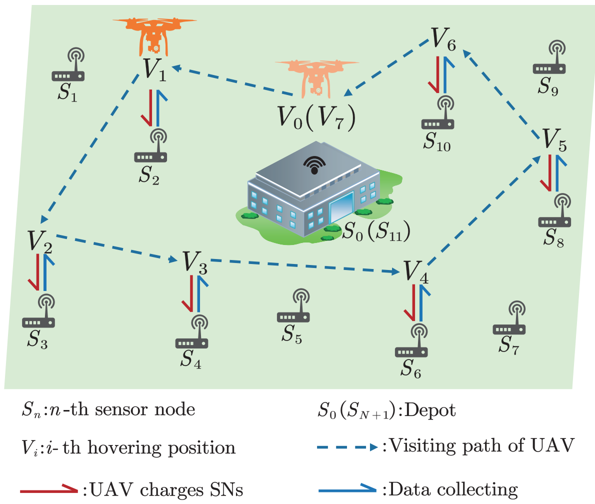


Fig. 1. UAV-assisted wireless-powered sensor networks

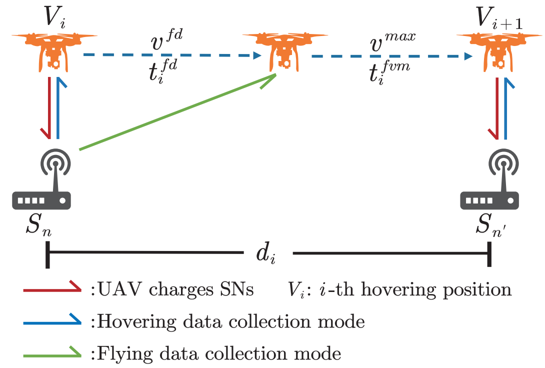


Fig. 2. Hovering and flying data collection model

a mixed data collection strategy combining hovering and flying modes, which is useful to reduce the AoI of the collected data and improve energy efficiency of the UAV during each flight. We formulate the UAV visiting planning problem as a mixed-integer nonlinear problem (MINLP) by comprehensively considering the visiting path and the mixed data collection strategy. Furthermore, we utilize the reformulation-linearization-technique (RLT) and alternating direction method of multipliers (ADMM) to tackle the difficulty of the joint optimization problem, which aims to minimize the average AoI of the collected data and meanwhile maximize the number of visiting SNs as well as the amount of data. The results show that the proposed ADMM-based visiting planning algorithm takes advantage of the mixed data collection strategy and can outperform other approaches [12], [13] in terms of system objective and energy efficiency.

## II. System Model

### A. System Architecture

The proposed UAV-assisted WPSN system is illustrated in Fig.1. A depot $S_0$ acts as a data center to perform data aggregation and remote monitoring from those sensing information acquisited by total $N$ ground SNs denoted by $\mathcal{S} = [S_1, S_2, \cdots, S_n, \cdots, S_N]$ and distributed in a large area. The UAV flies from the depot to visit a subset of SNs for data collection and meanwhile provide wireless charging to extend their service life. Specifically, we define that the UAV will first provide wireless charging and then collect the data from the visiting SN. Note that the UAV is equipped with limited battery capacity $E^U$, we assume that the UAV can visit *maximum* $I$ SNs during each flight and it will finally return to the depot for battery recharging. In this way, we also regard the depot as a virtual SN $S_{N+1}$. Furthermore, to provide continuous services, we assume that multiple UAVs could be deployed to fly and recharge alternately [14].

The **visiting planning** of a UAV is determined before departing from the depot. The visiting path can be presented as $V_0 \rightarrow V_1 \rightarrow \cdots \rightarrow V_i \rightarrow \cdots \rightarrow V_I \rightarrow V_{I+1}$, where $V_i$ means the $i$-th hovering position of the UAV. Denoting the 2D locations of $S_n$ as $\Phi(S_n)$, we know that both the starting and end positions of the UAV are the location of the depot, that is, $V_0 = \Phi(S_0)$ and $V_{I+1} = \Phi(S_{N+1})$. We further denote the *visiting path indicator* as $\mathbf{a} = [a_{n,i}]_{(N+1)\times(I+1)}$, where $a_{n,i} = 1$ means $S_n$ is the $i$-th SN visited by the UAV at location $V_i$. In this way, the distance between $V_i$ and $V_{i+1}$ can be calculated by

$$d_i = \sum_{n=1}^{N+1} \sum_{n'=1}^{N+1} a_{n,i} a_{n',i+1} \left\| \Phi(S_n) - \Phi(S_{n'}) \right\|_2. \quad (1)$$

### B. Data Collection Model

As shown in Fig. 2, we introduce a **mixed data collection strategy** combining hovering and flying modes. In *hovering mode*, a part of the data is collected when the UAV hovers above the visiting SN at $V_i$ while the remaining data is collected in *flying mode*, namely the period when the UAV flies directly from $V_i$ to $V_{i+1}$. We assume that the UAV flies at a fixed altitude $H$ and keeps a constant flying velocity $v^{fd}$ in flying mode. The $t_i^{hd}$ and $t_i^{fd}$ denote the elapsed time of data collection in hovering and flying modes, respectively.

We adopt the line-of-sight (LoS) transmission model for data collection. The channel gain of the wireless communication link between the UAV and $S_n$ under hovering mode and flying mode are given as:

$$\left|g_n^h\right|^2 = \beta_0 \cdot H^{-2}, \quad (2)$$

$$\left|g_n^f(t)\right|^2 = \beta_0 \cdot \sqrt{\left(v^{fd} t\right)^2 + H^2}^{\,-2}, \quad (3)$$

where $\beta_0$ represents the channel power gain at 1 m. Consequently, the data uploading rate under hovering and flying modes are given as

$$R_n^{hd} = B \log_2 \left( 1 + \frac{P_n^{up} \left|g_n^h\right|^2}{\sigma^2} \right), \quad (4)$$

$$R_{n,u}^{fd}(t) = B \log_2 \left( 1 + \frac{P_n^{up} \left|g_n^f(t)\right|^2}{\sigma^2} \right), \quad (5)$$

where $B$ is the channel bandwidth, $P_n^{up}$ is the transmission power of $S_n$, and $\sigma^2$ is the noise power.

### C. Flying Model

According to [15], we define the propulsion power consumption model of UAV as

$$P^{mov}(V) = P_0(1 + \frac{3V^2}{U_{tip}^2}) + P_1(\sqrt{1 + \frac{V^4}{4v_0^2}} - \frac{V^2}{2v_0^2})^{\frac{1}{2}} + \frac{1}{2} d_0 \rho s A V^3, \quad (6)$$

where $V$ is the flying velocity of the UAV and the rest of the parameters are constants related to a specific UAV. When the UAV is hovering, i.e., $V = 0$, the hovering power will be $P^{hov} = P_0 + P_1$. Similarly, when the UAV is flying, i.e, $V = v^{fd}$, the flying power will be $P^{fd} = P^{mov}(v^{fd})$. As shown in Fig. 2, we have the constraint $v^{fd} t_i^{fd} \leq d_i$. To ensure high data freshness, we assume that the UAV will fly the remaining distance from $V_i$ to $V_{i+1}$ at the end of data collection at maximum velocity $v^{max}$, and therefore the corresponding flying power will be $P^{vm} = P^{mov}(v^{max})$.

Note that the UAV flies from $V_i$ to $V_{i+1}$ combining hovering and flying modes for data collection, the elapsed time that the UAV flies at maximum velocity could be calculated by

$$t_i^{fvm} = \frac{d_i - v^{fd} t_i^{fd}}{v^{max}}. \quad (7)$$

Furthermore, the total flying time from $V_i$ to $V_{i+1}$ is given by

$$t_i^{fly} = \begin{cases} t_0^{fvm} = d_0 / v_{max}, & i = 0 \\ t_i^{fd} + t_i^{fvm}, & i \neq 0 \end{cases}. \quad (8)$$

### D. Energy Model

When $a_{n,1} = 1$, note that the UAV will charge $S_n$ once it arrives at $V_i$, the energy requirement of $S_n$ is defined by

$$E_{n,i}^{need} = P_n^{sr}(T' - u_n') + P_n^{up}\left(t_i^{hd} + t_i^{fd}\right). \quad (9)$$

The first term represents the sensing power consumption of $S_n$, where $P_n^{sr}$ denotes its data sensing power, $u_n'$ denotes the time stamp when last charging was completed, and $T'$ denotes the last time stamp when the UAV returned to the depot. The second term represents its energy consumption of data uploading during hovering and flying mode. So far, the charging time at $V_i$ can be presented by

$$t_i^{chg} = \sum_{n=1}^{N} \frac{a_{n,i} E_{n,i}^{need}}{\eta' \left|g_n^h\right|^2 P^{chg}}, \quad (10)$$

where $\eta'$ is energy loss rate and $P^{chg}$ is the maximum charging power of UAV.

We can calculate the energy consumed by UAV for charging, hovering, and flying by

$$E_i^{chg} = P^{chg} t_i^{chg}, \quad (11)$$

$$E_i^{hov} = P^{hov}(t_i^{chg} + t_i^{hd}), \quad (12)$$

$$E_i^{fly} = \begin{cases} P^{vm} t_0^{fvm}, & i = 0 \\ P_i^{fd} t_i^{fd} + P^{vm} t_i^{fvm}, & i \neq 0 \end{cases} \quad (13)$$

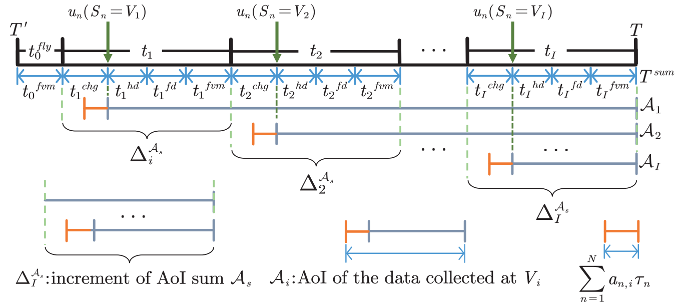


Fig. 3. AoI model of data collection

Therefore, its total energy consumption during a flight will be

$$E_s = E_0^{fly} + \sum_{i=1}^{I} E_i^{chg} + E_i^{hov} + E_i^{fly}. \quad (14)$$

We further define the energy efficiency rate of a flight as

$$\eta = \frac{\sum_{i=1}^{I} \left[P^{chg} t_i^{chg} + P^{hov}(t_i^{chg} + t_i^{hd}) + P^{fd} t_i^{fd}\right]}{E_s}. \quad (15)$$

### E. AoI Model

To better quantify the *freshness* of data, we introduce $\tau_n$ to represent the data generation time of size $D_n$ at $S_n$ with sampling rate $r_n^{sr}$, that is,

$$\tau_n = \frac{D_n}{r_n^{sr}}. \quad (16)$$

The total amount of the collected data in a flight will be $\mathcal{D}_s = \sum_i^I \sum_{n=1}^N a_{n,i} D_n$. Besides, we define $u_n$ as the time stamp when the UAV starts to collect data from $S_n$ and $T$ as the time stamp when the UAV returns to the depot. The time stamp $T$ is calculated by

$$T = T' + t_0^{fly} + \sum_{i=1}^{I} t_i, \quad (17)$$

where $t_i = t_i^{chg} + t_i^{hd} + t_i^{fd} + t_i^{fvm}$.

We introduce AoI as the key performance metric to describe the freshness of the collected data. Let $\mathcal{A}_i$ be AoI of the collected data from the visiting SN at $V_i$:

$$\mathcal{A}_i = \sum_{n=1}^{N} a_{n,i}\left(T - u_n + \tau_n\right). \quad (18)$$

The AoI sum of all collected data in a flight will be $\mathcal{A}_s = \sum_{i=1}^I \mathcal{A}_i$. As illustrated in Fig. 3, the increment of $\mathcal{A}_s$ after visiting the SN at $V_i$ is formulated as

$$\Delta_i^{\mathcal{A}_s} = i \cdot \left(t_i^{chg} + t_i^{hd} + t_i^{fd} + t_i^{fvm}\right) - t_i^{chg} + \sum_{n=1}^{N} a_{n,i} \tau_n. \quad (19)$$

## III. Problem Formulation And Solution

In the proposed UAV-assisted WPSN, we aim to minimize the average AoI of the collected data and meanwhile maximize the number of visiting SNs as well as the amount of data. In case some SNs may not be visited for too long, we provide a *penalty mechanism* to guarantee the system fairness. After a UAV flight, the penalty will be updated by

$$\mathcal{P}_s = \sum_{n=1}^{N} \left( 1 - \sum_{i=1}^{I} a_{n,i} \right) \left( T' - u'_n \right). \tag{20}$$

### A. Problem Formulation

To optimize the visiting path $\mathbf{a}$ and the data collection strategy, i.e., $\mathbf{t}^{hd}$ and $\mathbf{t}^{fd}$, we formulated the AoI-aware UAV visiting planning problem as follows:

$$\begin{aligned}
\mathcal{P}0 : &\min_{I,\mathbf{a},\mathbf{t}^{hd},\mathbf{t}^{fd}} \frac{\alpha \mathcal{A}_s + \gamma \mathcal{P}_s}{\beta \mathcal{D}_s} \qquad (21)\\
\text{s.t.C1} : &\begin{cases} \mathrm{I} : \sum_{n=1}^{N} a_{n,i} = 1, \quad \forall i \in \{1,...,I\} \\ \mathrm{II} : \sum_{i=1}^{I} a_{n,i} \le 1, \quad \forall n \in \{1,...,N\} \\ \mathrm{III} : \sum_{i=1}^{I+1} a_{n,i} = 1, \quad n = N+1 \\ \mathrm{IV} : \sum_{n=1}^{N+1} a_{n,i} = 1, \quad i = I+1 \\ \mathrm{V} : a_{N+1,I+1} = 1, \end{cases}\\
\text{C2} : &\begin{cases} \mathrm{I} : t_i^{hd} \ge 0, \quad \forall i \in \{1,...,I\} \\ \mathrm{II} : 0 \le v^{fd} t_i^{fd} \le l_i^{max}, \quad \forall i \in \{1,...,I\} \end{cases}\\
\text{C3} : &l_i^{max} = \min\left\{d_{com}^{max}, d_i\right\}, \quad \forall i \in \{1,...,I\}\\
\text{C4} : &D_i \le \sum_{n=1}^{N} a_{n,i} [t_i^{hd} R_n^{hd} + \int_0^{t_i^{fd}} R_{n,u}^{fd}(t) dt],\\
&\forall i \in \{1,...,I\}\\
\text{C5} : &0 \le E_s \le E^U\\
&I \in \{0,...,N\}, \quad \forall a_{n,i} \in \{0,1\},\\
&\forall n \in \{1,...,N+1\}, \quad \forall i \in \{1,...,I+1\}
\end{aligned}$$

where $\alpha, \beta, \gamma$ represent weighting factors, and $d_{com}^{max}$ is the horizontal distance of the maximum communication distance between the UAV and SNs. The visiting path constraint C1 guarantees that an SN can only be visited once during each flight. The constraints C2 and C3 limit the data collection distance between the UAV and SNs. The constraint C4 indicates the UAV will collect all data generated by SNs. The energy consumption of UAV is regulated by the constraint C5. We find out the problem $\mathcal{P}0$ is an MINLP problem due to the quadratic term constraints and mixed optimization variables.

In order to reduce the difficulty, we utilize the RLT [16] to tackle the second-order term $a_{n,i} a_{n',i+1}$. We introduce an auxiliary variable $\mathbf{b} = [b_{nn'i}]_{(N+1)\times(N+1)\times I}$, which is constrained by

$$\text{C6} : \begin{cases} \mathrm{I} : b_{nn'i} \le a_{n,i}, \\ \mathrm{II} : b_{nn'i} \le a_{n',i+1}, \\ \mathrm{III} : b_{nn'i} \ge a_{n,i} + a_{n',i+1} - 1. \\ \forall b_{nn'i} \in \{0,1\} \\ \forall n, n' \in \{1,...,N+1\}, \forall i \in \{1,...,I\} \end{cases} \tag{22}$$

Besides, we introduce two 0-1 variables $x, y$ and a large number $\mathcal{M}$ to linearize the min function in the constraints C3.

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**Algorithm 1:** ADMM-Based Visiting Planning

**Input:** $\mathbf{a}^{(0)}$, $\mathbf{b}^{(0)}$, $\mathbf{t}^{hd(0)}$, $\mathbf{t}^{fd(0)}$(not necessarily feasible for $\mathcal{P}1$), $\lambda^{(0)} = \rho = 1$; Set $k = 0$, $f^* = \infty$.

```
for I = 1 : N do
    while k ≤ T and stopping criterion is not met do
        Solve the SP1 and obtain a^(k+1), b^(k+1);
        Solve the SP2 and obtain t^hd(k+1), t^fd(k+1);
        Update the Lagrange dual multipliers λ^(k+1);
        k = k + 1;
    end
    f(I) = L_1(I, a^(k), b^(k), t^hd(k), t^fd(k));
    if f(I) ≤ f* then
        f* = f(I), I* = I, a* = a^(k), b* = b^(k),
          t^hd* = t^hd(k), t^fd* = t^fd(k);
    end
end
```

**Output:** $\mathbf{I}^*$, $\mathbf{a}^*$, $\mathbf{b}^*$, $\mathbf{t}^{hd*}$, $\mathbf{t}^{fd*}$.

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In this way, the constraints C3 and C5 can be reformulated as

$$\text{C3}' : \begin{cases} \mathrm{I} : l_i^{max} \le d_i, \\ \mathrm{II} : l_i^{max} \le d_{com}^{max}, \\ \mathrm{III} : d_i \le l_i^{max} - \mathcal{M}(1-x), \\ \mathrm{IV} : d_{com}^{max} \le l_i^{max} - \mathcal{M}(1-y), \\ \mathrm{V} : x + y \ge 1, \\ \forall x, y \in \{0,1\}, \quad \forall i \in \{1,...,I\} \end{cases} \tag{23}$$

$$\text{C5}' : 0 \le E'_s \le E^U, \tag{24}$$

where the objective function in $\mathcal{P}0$ and $E_s$ are replaced by (25) and (26), respectively. So far, the original problem $\mathcal{P}0$ can be reformulated as

$$\begin{aligned}
\mathcal{P}1 : &\min_{I,\mathbf{a},\mathbf{b},\mathbf{t}^{hd},\mathbf{t}^{fd}} L_1 \qquad (27)\\
&\text{s.t. C1, C2, C3}', \text{C4, C5}', \text{C6}\\
&I \in \{0,...,N\}, \quad \forall a_{n,i} \in \{0,1\}, \quad \forall b_{nn'i} \in \{0,1\}\\
&\forall n, n' \in \{1,...,N+1\}, \quad \forall i \in \{1,...,I+1\}
\end{aligned}$$

### B. ADMM-Based Solution

Furthermore, we relax $\text{C5}'$ as

$$\text{C5}'' : \begin{cases} \mathrm{I} : E'_s + u = E^U \\ \mathrm{II} : u \ge 0 \end{cases}, \tag{28}$$

and then construct a Lagrangian multiplier formula to $\mathcal{P}1$. Let $\lambda$ be the Lagrange multiplier and $\rho$ be the penalty factor. The augmented Lagrangian for $\mathcal{P}1$ is derived as

$$\begin{aligned} L_\rho = &L_1 + \lambda\left(E'_s + u - E^U\right) \\ &+ \frac{\rho}{2}\left\| max\left(E'_s - E^U, 0\right)\right\|^2. \end{aligned} \tag{29}$$

Currently, we observe that the variables $\mathbf{a}$, $\mathbf{b}$, $\mathbf{t}^{hd}$, $\mathbf{t}^{fd}$ could be separable in $\mathcal{P}1$. Therefore, we apply the ADMM technique [17], which is a simple yet well-designed method suited for distributed convex optimization problems, to separate $\mathcal{P}1$ into two subproblems, where $\mathcal{SP}1$ is a 0-1 integer problem to optimize the visiting path of the UAV and $\mathcal{SP}2$ is a non-convex optimization problem with non-linear constraints, focused on

$$L_1 = \sum_{i=1}^{I}\sum_{n=1}^{N} a_{n,i}\Lambda_{n,i} + \sum_{i=1}^{I}\sum_{n=1}^{N}\sum_{n'=1}^{N} b_{nn'i}\Upsilon_{nn'i} + \sum_{i=1}^{I}\left(\Xi_i t_i^{hd} + \Psi_i t_i^{fd}\right) + \sum_{n=1}^{N}\Theta_n. \tag{25}$$

$$E_s' = \sum_{i=1}^{I}\sum_{n=1}^{N} a_{n,i}\vartheta_n + \sum_{i=1}^{I}\sum_{n=1}^{N}\sum_{n'=1}^{N} b_{nn'i}\xi_{nn'} + \sum_{n=1}^{N} a_{n,1}\zeta_n + \sum_{i=1}^{I}\left(\psi_1 t_i^{hd} + \psi_2 t_i^{fd}\right). \tag{26}$$

TABLE I
LIST OF KEY SIMULATION PARAMETERS

| Parameter | Value |
|---|---|
| $H$, $v^{max}$ | 10m, 19m/s |
| $P_0$,$P_1$ [15] | 84.12W,84.36W |
| $P^{chg}$, $P_n^{up}$, $P_n^{sr}$ | 10W, 1mW, 22.5μW |
| $B$, $\beta_0$, $\sigma^2$ [12] | 20KHz, $-10$dB, $-90$dBm |
| $D_i$, $r_n^{sr}$ | 2MB, $N(\mu = 10, \sigma^2 = 2)$KB/s |
| $\alpha, \beta, \gamma$ | $0.5, 0.3, 0.2$ |
| $\{\epsilon^a, \epsilon^b\}$, $\{\epsilon_1^t, \epsilon_2^t, \epsilon^\lambda\}$ | $10^{-3}, 10^{-5}$ |

determining the data collection strategy. In the $k$-th iteration, $\mathcal{SP}1$ and $\mathcal{SP}2$ are presented as

$$\begin{aligned} \mathcal{SP}1 : &\min_{\mathbf{a},\mathbf{b}} L_\rho\left(\mathbf{a}, \mathbf{b}, \mathbf{t}^{hd(k)}, \mathbf{t}^{fd(k)}, \lambda^{(k)}\right) \\ &\text{s.t. C1, C6} \quad \forall a_{n,i} \in \{0,1\}, \quad \forall b_{nn'i} \in \{0,1\} \end{aligned} \tag{30}$$

$$\begin{aligned} \mathcal{SP}2 : &\min_{\mathbf{t}^{hd},\mathbf{t}^{fd}} L_\rho\left(\mathbf{a}^{(k+1)}, \mathbf{b}^{(k+1)}, \mathbf{t}^{hd}, \mathbf{t}^{fd}, \lambda^{(k)}\right) \\ &\text{s.t. C2, C3}', \text{C4} \end{aligned} \tag{31}$$

The full description of the proposed ADMM-based algorithm is presented in Algorithm 1. The Lagrange multiplier $\lambda$ is updated by

$$\begin{cases} E^\lambda = E_s'(\mathbf{a}^{(k+1)}, \mathbf{b}^{(k+1)}, \mathbf{t}^{hd(k+1)}, \mathbf{t}^{fd(k+1)}) \\ \lambda^{(k+1)} = \lambda^{(k)} + \rho\left(\max\left(E^\lambda - E^U, 0\right)\right) \end{cases}, \tag{32}$$

and the stopping criterion is defined as

$$\begin{gathered} \left\|\mathbf{a}^{(k)} - \mathbf{a}^{(k-1)}\right\|_2 \le \epsilon^a, \quad \left\|\mathbf{b}^{(k)} - \mathbf{b}^{(k-1)}\right\|_2 \le \epsilon^b, \\ \left\|\mathbf{t}^{hd(k)} - \mathbf{t}^{hd(k-1)}\right\|_2 \le \epsilon_1^t, \quad \left\|\mathbf{t}^{fd(k)} - \mathbf{t}^{fd(k-1)}\right\|_2 \le \epsilon_2^t, \\ \left\|\lambda^{(k)} - \lambda^{(k-1)}\right\|_2 \le \epsilon^\lambda. \end{gathered} \tag{33}$$

By alternately solving these two subproblems, we can eventually obtain the optimal solution of the problem $\mathcal{P}1$. This alternating process allows us to leverage the advantages of the ADMM and finally converge to the optimal visiting path and data collection strategy.

## IV. SIMULATION RESULTS

Simulation results are provided to verify the performance of the proposed UAV-assisted visiting planning. We consider that multiple SNs are randomly distributed in the WPSN to perform uninterrupted data sensing. Several key parameters are listed in Table I. Specifically, we model the UAV according to DJI Air 2s with 41.4Wh battery capacity and maximum flying velocity $v^{max} = 19$m/s. The maximum communication distance between UAV and SNs is set as 100m, therefore we have $d_{com}^{max} = \sqrt{100^2 - H^2}$m, where $H = 10$m is the flight altitude of UAV. We compare five approaches: 1) *Greedy-mixed*, in which the UAV selects the nearest SN to visit each time; 2) *DP-mixed*, dynamic programming-based approach proposed in [12]; 3) *GA-mixed*, genetic algorithm-based approach proposed in [13]; 4) *Proposed-hover* and 5) *Proposed-mixed*, the proposed approach. Specifically, both the *DP-mixed* and *GA-mixed* approaches do not consider the energy consumption of the UAV. The "*hover*" and "*mixed*" indicate the corresponding approach applies pure data collection strategy with hovering mode and the mixed data collection strategy, respectively.

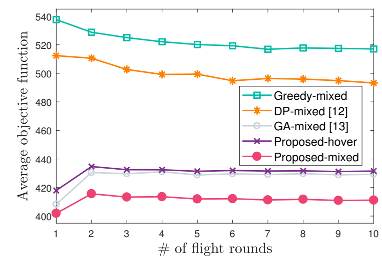



Fig. 4. Performance versus the rounds of flights

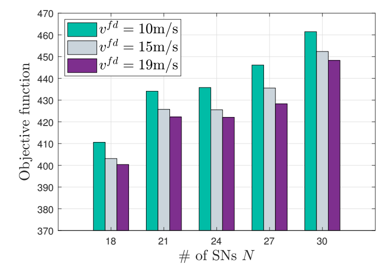
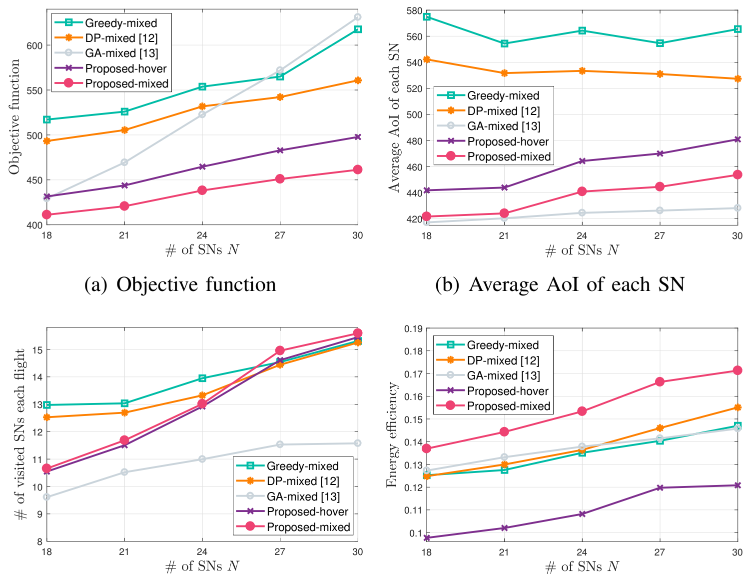



Fig. 5. Performance versus different flying velocity $v^{fd}$ (*Proposed-mixed*)

As shown in Fig. 4, we find out that the experimental results tend to stabilize after the UAV completes 7 rounds of flights. Therefore, in the rest of the experiments, we evaluate 7 rounds of flights in each experiment. Besides, we conduct repeated experiments under *Proposed-mixed* to determine the best value of the velocity $v^{fd}$ in flying mode. As shown in Fig. 5, we observe that the scenario with maximum flying, i.e., $v^{fd} = 19$m/s, can achieve the best performance.

In addition, we discussed the performance versus the number of SNs in Fig. 6. In general, the objective function, the number visited of SNs each flight and energy efficiency increase as the number of SNs grows. The *Proposed-mixed* outperforms other approaches in terms of objective function and energy efficiency. The *Proposed-mixed* is better than *Proposed-hover* in all aspects, which confirms the outstanding of the mixed data collection strategy. Specifically, *GA-mixed*




(a) Objective function (b) Average AoI of each SN

(c) # of visited SNs each flight (d) Energy efficiency

Fig. 6. Performance versus # of SNs $N$

can achieve a smaller average AoI of each SN than *Proposed-mixed*, as shown in Fig. 3. This is because the fewest SNs are visited in *GA-mixed* during each flight. According to our definition of AoI in Fig. 3, more visited SNs will cause rapid growth of AoI increment, that is, more visited SNs will lead to higher average AoI.

## V. Conclusions

In this paper, we study the energy-limited UAV visiting planning problem to assist in data collection of the AoI-aware WPSN. We proposed an ADMM-based visiting planning algorithm to jointly optimize the visiting path and the mixed data collection strategy. The results show the proposed algorithm can outperform other approaches in terms of system objective and energy efficiency.

## References


[1] Y. Zhang, C.-Y. Wang, and H.-Y. Wei, "Parking reservation auction for parked vehicle assistance in vehicular fog computing," *IEEE transactions on vehicular technology*, vol. 68, no. 4, pp. 3126–3139, 2019.

[2] S. Li, A. Wang, G. Sun, and L. Liu, "Improving charging performance for wireless rechargeable sensor networks based on charging uavs: a joint optimization approach," in *2020 IEEE Symposium on Computers and Communications (ISCC)*, 2020, pp. 1–7.

[3] J. Wang, C. Jin, Q. Tang, N. N. Xiong, and G. Srivastava, "Intelligent ubiquitous network accessibility for wireless-powered mec in uav-assisted b5g," *IEEE Transactions on Network Science and Engineering*, vol. 8, no. 4, pp. 2801–2813, 2021.

[4] C. Zhao, J. Liu, M. Sheng, W. Teng, Y. Zheng, and J. Li, "Multi-uav trajectory planning for energy-efficient content coverage: A decentralized learning-based approach," *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 10, pp. 3193–3207, 2021.

[5] K. K. Nguyen, T. Q. Duong, T. Do-Duy, H. Claussen, and L. Hanzo, "3d uav trajectory and data collection optimisation via deep reinforcement learning," *IEEE Transactions on Communications*, vol. 70, no. 4, pp. 2358–2371, 2022.

[6] Z. Xiong, Y. Zhang, W. Y. B. Lim, J. Kang, D. Niyato, C. Leung, and C. Miao, "Uav-assisted wireless energy and data transfer with deep reinforcement learning," *IEEE Transactions on Cognitive Communications and Networking*, vol. 7, no. 1, pp. 85–99, 2021.

[7] Y. Yu, J. Tang, J. Huang, X. Zhang, D. K. C. So, and K.-K. Wong, "Multi-objective optimization for uav-assisted wireless powered iot networks based on extended ddpg algorithm," *IEEE Transactions on Communications*, vol. 69, no. 9, pp. 6361–6374, 2021.

[8] R. D. Yates, Y. Sun, D. R. Brown, S. K. Kaul, E. Modiano, and S. Ulukus, "Age of information: An introduction and survey," *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 5, pp. 1183–1210, 2021.

[9] H. Hu, K. Xiong, G. Qu, Q. Ni, P. Fan, and K. B. Letaief, "Aoi-minimal trajectory planning and data collection in uav-assisted wireless powered iot networks," *IEEE Internet of Things Journal*, vol. 8, no. 2, pp. 1211–1223, 2021.

[10] L. Liu, K. Xiong, J. Cao, Y. Lu, P. Fan, and K. B. Letaief, "Average aoi minimization in uav-assisted data collection with rf wireless power transfer: A deep reinforcement learning scheme," *IEEE Internet of Things Journal*, vol. 9, no. 7, pp. 5216–5228, 2022.

[11] J. Hu, H. Zhang, L. Song, R. Schober, and H. V. Poor, "Cooperative internet of uavs: Distributed trajectory design by multi-agent deep reinforcement learning," *IEEE Transactions on Communications*, vol. 68, no. 11, pp. 6807–6821, 2020.

[12] Z. Jia, X. Qin, Z. Wang, and B. Liu, "Age-based path planning and data acquisition in uav-assisted iot networks," in *2019 IEEE International Conference on Communications Workshops (ICC Workshops)*, 2019, pp. 1–6.

[13] T. Yang, Y. Hu, X. Yuan, and R. Mathar, "Genetic algorithm based uav trajectory design in wireless power transfer systems," in *2019 IEEE Wireless Communications and Networking Conference (WCNC)*, 2019, pp. 1–6.

[14] C. Huang, Z. Ming, and H. Huang, "Drone stations-aided beyond-battery-lifetime flight planning for parcel delivery," *IEEE Transactions on Automation Science and Engineering*, pp. 1–11, 2022.

[15] G. Chen, X. B. Zhai, and C. Li, "Joint optimization of trajectory and user association via reinforcement learning for uav-aided data collection in wireless networks," *IEEE Transactions on Wireless Communications*, pp. 1–1, 2022.

[16] Y. Zhang, J.-H. Liu, C.-Y. Wang, and H.-Y. Wei, "Decomposable intelligence on cloud-edge iot framework for live video analytics," *IEEE Internet of Things Journal*, vol. 7, no. 9, pp. 8860–8873, 2020.

[17] W.-C. Liao, M. Hong, H. Farmanbar, X. Li, Z.-Q. Luo, and H. Zhang, "Min flow rate maximization for software defined radio access networks," *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 6, pp. 1282–1294, 2014.