Joint Scheduling and Trajectory Design for UAV-Aided Wireless Power Transfer System

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Abstract. In this paper, we focus on an unmanned aerial vehicle (UAV)-aided wireless power transfer (WPT) system, where an energy transmitter is deployed on UAV and sends wireless energy to multiple energy-limited sensor nodes (SNs) for energy supplement. How to exploit the UAV's mobility via trajectory design and adopt suitable scheduling scheme of SNs will directly influence the whole charging efficiency over a given charging period. From the perspective of fairness among SNs, our aim is to maximize the minimum energy received by all SNs by jointly optimizing the UAV's trajectory and SNs' scheduling scheme with the UAV's maximum speed constraint as well as the initial/final location

This work was supported in part by the National Natural Science Foundation of China under Grant 61801435, Grant 61801243 and Grant U1833203, in part by the Project funded by China Postdoctoral Science Foundation under Grant 2018M633733, in part by the Scientific and Technological Key Project of Henan Province under Grant 182102210449 and Grant 192102210246, in part by the Scientific Key Research Project of Henan Province for Colleges and Universities under Grand 19A510024, in part by Science and Technology Innovation Teams of Henan Province for Colleges and Universities (No. 17IRTSTHN014), in part by the Natural Science Research Project of Jiangsu Province for Colleges and Universities (No. 16KJB510008).

V. C. M. Leung et al. (Eds.): 5GWN 2019, LNICST 278, pp. 3–17, 2019.
https://doi.org/10.1007/978-3-030-17513-9_1

constraint. However, the established problem is in a non-convex mixed integer form, which is difficult to tackle. Therefore, we first decompose the original problem into two subproblems and then develop an efficient iterative algorithm by using the successive convex optimization technique, which leads to a suboptimal solution. Numerical results are provided to demonstrate the superiority of our proposed algorithm over the benchmarks.

Keywords: Unmanned aerial vehicle (UAV)
Wireless power transfer (WPT) · SNs scheduling
Trajectory optimization

1 Introduction

Wireless senor networks (WSNs) have been widely used in every aspect of society due to its low cost and convenient deployment on variety scenarios, such as environmental monitor, biomedical observation, data collection and so on [1,8]. However, the vast majority of sensor nodes (SNs) always have limited physical size, which leads to the lack of energy storage capacity. Therefore, how to charge the SNs plays on important role on prolonging the effective lifetime of the WSNs. Many attentions have paid to explore the natural energy for the SNs' energy harvesting, such as solar, thermoelectric or other physical phenomena [3,4,6,13]. Whereas, such schemes are usually subject to the weather and environment conditions to a large extent.

An emerging and promising solution is to utilize the radio-frequency (RF) transmission technique, namely wireless power transfer (WPT) system, whose advantage lies in that the SNs can directly harvest the energy from the energy transmitter (ET) via the RF signal. However, the RF signals will suffer from due serious path loss over long propagation distance, which results in severe performance loss in practical WPT systems in terms of the end-to-end WPT efficiency and the energy supply range. Consequently, in order to improve the WPT efficiency and provide ubiquitous wireless energy transmission to massive energy-constraint SNs, a large number of ETs should be deployed to shorten the distance between the SNs and ETs. Nevertheless, the corresponding deployment cost of ETs will increase dramatically and has a significant impact on the large-scale implementation of WPT systems.

Fortunately, the application of unmanned aerial vehicle (UAV) as mobile ET gives birth to a radically novel architecture for the WPT systems [12]. Exactly speaking, the ET is mounted on UAV for charging SNs and can rely on the UAV's flexible mobility to adjust its location arbitrarily in order to experience the favorable environment condition, which is more preponderant compared with the conventional ETs with fixed locations. Furthermore, low manufacturing cost of UAV as well as device miniaturization facilitate the implementations of the UAV-aided WPT system. In fact, low-altitude UAVs carrying communication transceiver has already been explored in recent studies [9,10,15], wherein UAVs are employed as aerial base stations or relays to boost the performance of terrestrial wireless communication systems. By optimizing the UAV's trajectory and use distance-based user scheduling, the communication link quality will be significantly improved by shortening the distance between the UAV and its served users, which makes the overall system throughput substantially promoted [9,10,15].

Inspired by aforesaid observations, we investigate a UAV-aided WPT system with multiple SNs. Precisely, a UAV is deployed as ET that flies over a specified area to help charge all the distributed ground SNs according to a proper scheduling manner, which is different from the previous work [12] focusing on a UAV-enabled WPT system with a special two users case. In this paper, our goal is to maximize the minimum total energy of SNs by jointly optimizing the UAV trajectory and designing the SN's wake-up schedule, with maximum speed, initial/final location, and energy conversion threshold constraints. Kindly note that with such a wake-up scheduling mechanism, a SN can remain in the sleep state without energy conversion device working until it receives the waking up beacon signal with good RF signal strength from the nearby UAV, at which time it will wake up and start harvesting the wireless energy from the UAV, and return to the sleep state after the transmission [7,16]. This is a useful technique to save the energy consumption of SNs and improve the charging efficiency by shutting down the energy conversion processing when the RF signal strength is not strong enough. This is different from the existing studies [10,11], which assumes that each SN keeps its energy conversion device running all the time as the UAV flies. As we know, the wireless channels between the SNs and the moving UAV fluctuate fast and drastically due to the UAV's flexible and high mobility. Thus, the received RF signal strength cannot always satisfy the energy conversion threshold, which will make the charging efficiency quiet low if the energy conversion device runs continuously. This is because the SN in waking-up state needs energy to maintain its normal operation.

Our design is formulated as a mixed-integer non-convex optimization problem, which is difficult to be optimally solved. By decomposing the original problem into two sum-problems and applying the successive convex optimization technique, an efficient iterative algorithm is proposed to find a suboptimal solution for our design. Numerical results show that the proposed scheme outperforms the benchmark schemes with static or simple straight trajectory of the UAV.

This paper is organized as follows. Section 2 introduces the system model. Section 3 proposes the iterative algorithm to solve the formulated problem. The numerical results and comparisons are presented in Sect. 4. Finally, the conclusion is given in Sect. 5.

2 System Model

As shown in Fig. 1, K single-antenna senor nodes (SNs) are distributed on the ground in a specific area with fixed locations and a single-antenna UAV broadcasts wireless energy to charge the nodes. The UAV travels along unidirectional trajectory with the practical maximum UAV speed constraint. It is assumed that

UAV flies at a fixed altitude H meters ('m' for short) and the maximum flying speed $V_{\max}$ meter/second ('m/s' for short). Meanwhile, the total flying time of UAV is denoted as time horizon T second ('s' for short).

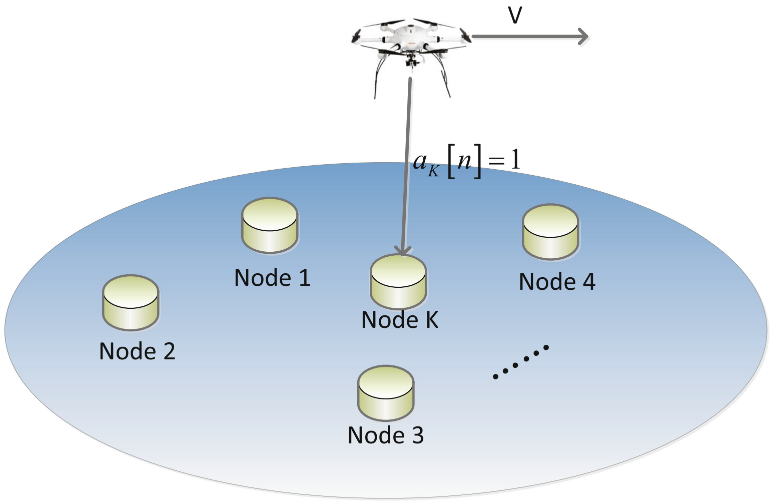

Fig. 1. UAV-aided WPT system with multiple SNs.

For the sake of mathematical description, we set up a three-dimensional Cartesian coordinate system, with all dimensions measured in meters, where the horizontal coordinate of node k is denoted by $\mathbf{w}_k = (x_k, y_k)^{\mathrm{T}} \in \mathbb{R}^{2\times 1}$, $k = 1, \ldots, K$, and the horizontal coordinate of UAV over time instant t is denoted by $\mathbf{q}(t) = (x(t), y(t))^{\mathrm{T}} \in \mathbb{R}^{2\times 1}$, $0 \le t \le T$. For ease of exposition, time horizon T is equally divided into N time slots with each slot duration δ. As such, the UAV trajectory $\mathbf{q}(t)$ over time T can be approximately denoted by N-length sequences $\{\mathbf{q}[n]\}_{n=1}^{N}$. Note that the slot duration δ should be sufficient small so that the UAV's location can be assumed to be unchanged within this slot [5,14].

Herein, we assume that the initial and landing locations of UAV are predefined as follows

$$\mathbf{q}[1] = \mathbf{q}_0,\ \mathbf{q}[N] = \mathbf{q}_{\mathrm{F}}, \tag{1}$$

where $\mathbf{q}_0$ and $\mathbf{q}_{\mathrm{F}}$ denote the UAV's initial and landing location coordinates, respectively. In practical, UAV usually has a maximum flying speed. Thus, in each time slot, UAV trajectory should be subject to the following constraint

$$\|\mathbf{q}[n+1] - \mathbf{q}[n]\|^2 \le (V_{\max}\delta)^2, n = 1, \ldots, N-1 \tag{2}$$

where $\|.\|$ means 2-norm calculation. It indicates that the maximum distance of UAV traveled within a time slot cannot be exceeded $V_{\max}\delta$.

From [9,12,14], it can be found that the communication channel from UAV to each node is always dominated by line-of-sight (LoS) link due to the sufficient scattering environment around UAV in the air. Thus, the channel gain from UAV to node k at time slot n follows the free-space path loss model, which is given by

$$h_k[n] = \frac{\beta_0}{d_k^2[n]} = \frac{\beta_0}{\|\mathbf{q}[n] - \mathbf{w}_k\|^2 + H^2}, \tag{3}$$

where $d_k[n]$ denotes the distance between UAV and node k at time slot n, and β_0 denotes the received power at the reference distance $d = 1\,\mathrm{m}$ for a transmission power of 1 W.

2.1 Wake-Up Scheduling Criteria for Energy Harvesting

Herein, we adopt the sleep and wake-up mechanism, where indicates that the node can be waked up to connect with UAV at any time if and only if the received wireless signal strength satisfies the required energy conversion threshold [16].

Define time-varying wake-up scheduling variable $a_k[n]$, which indicates that node k is waked up at time slot n if $a_k[n] = 1$, and otherwise $a_k[n] = 0$. For notation simplicity, we define the UAV's trajectory set and wake-up scheduling set as $Q = \{\mathbf{q}[n], \forall n\}$ and $A = \{a_k[n], \forall k, n\}$, respectively. Assume that the transmit power of UAV is P, and then, the harvested power by node k at time slot n is given by

$$Q_k[n] = \eta_k P h_k[n] = \frac{\eta_k P \beta_0}{\|\mathbf{q}[n] - \mathbf{w}_k\|^2 + H^2}, \tag{4}$$

where $\eta_k \in (0, 1)$ denotes the energy harvesting efficiency at the receiver k.

Then, the total energy of node k during the duration time T can be expressed as

$$E_k = \underbrace{\delta \sum_{n=1}^{N} a_k[n] Q_k[n]}_{\text{harvested energy}} + \underbrace{\tilde{E}_k}_{\text{residual energy}}, \tag{5}$$

where the first term denotes the harvested energy and $\tilde{E}_k$ means the residual energy of node k, which is assumed to follow independent Poisson distribution with expectation λ_k.

2.2 Problem Formulation

To achieve the fairness among SNs, we aim at maximizing the minimum harvested energy by jointly designing the SNs wake-up scheduling and UAV trajectory with UAV speed, initial/final locations and energy conversion threshold constraints over a finite horizon time T. The minimum harvested energy is defined as $\theta(Q,A) = \min_{\forall k} E_k$. Hence, the involved problem can be established as

$$
\begin{aligned}
(\text{P1}):\quad & \max_{\{Q,A,\theta\}} \ \theta \\
\text{s.t.}\quad & E_k \geq \theta, \quad \forall k, && (6)\\
& Q_k[n] \geq a_k[n]\xi, \ \ \forall k,n, && (7)\\
& a_k[n] \in \{0,1\}, \quad \forall k,n, && (8)\\
& \left\|\mathbf{q}[n+1]-\mathbf{q}[n]\right\|^2 \leq (V_{\max}\delta)^2, \\
& \qquad\qquad n = 1,\ldots,N-1, && (9)\\
& \mathbf{q}[1] = \mathbf{q}_0, && (10)\\
& \mathbf{q}[N] = \mathbf{q}_{\mathrm{F}}, && (11)
\end{aligned}
$$

Due to the coupled variables in (6) and the involved binary variables, problem (P1) is a non-convex mixed integer optimization problem, which cannot be directly solved by standard convex optimization techniques.

3 Suboptimal Solution to Problem (P1)

To solve problem (P1), we decompose it into two subproblems to optimize the UAV trajectory and SNs scheduling scheme separately. Then, an iterative algorithm is proposed via alternately optimizing the two suboptimal problems. Finally, the convergence of the proposed algorithm is analyzed.

3.1 Wake-Up Scheduling Optimization

In this section, we consider the subproblem of (P1) for optimizing wake-up scheduling A by assuming UAV's trajectory Q is fixed. As a result, the problem (P1) is relaxed to the following problem, which is given by

$$
\begin{aligned}
(\text{P1.1}):\quad & \max_{\{A,\theta\}} \ \theta \\
\text{s.t.}\quad & E_k \geq \theta, \quad \forall k, && (12)\\
& Q_k[n] \geq a_k[n]\xi, \ \ \forall k,n, && (13)\\
& a_k[n] \in \{0,1\}, \quad \forall k,n. && (14)
\end{aligned}
$$

Note that problem (P1.1) is a classic linear 0-1 programming problem, which have a high complexity with the number of variables increasing. Thus, we first relax the binary variable $a_k[n]$ into continuous variable. That is, the constraint (14) is replaced by $0 \leq a_k[n] \leq 1$. Thus, the problem (P1.1) is recast into a linear programming problem, denoted as $(\bar{\text{P}}1.1)$. Furthermore, it can be proved that the optimal wake-up scheduling solution to problem $\left(\bar{\mathrm{P}}1.1\right)$ is either 1 or 0, which indicates the problem $\left(\bar{\mathrm{P}}1.1\right)$ and (P1.1) have same solutions. Then, we have the following Theorem.

Theorem 1. *Problem* $\left(\bar{\mathrm{P}}1.1\right)$ *is equivalent to problem* (P1.1).

Proof. The corresponding partial lagrangian function of problem $\left(\bar{\mathrm{P}}1.1\right)$ can be expressed as

$$\begin{aligned}
&\mathcal{L}\left(a_k\left[n\right], \theta, \nu_k, \mu_{n,k}\right)\\
&= \theta + \sum_{n=1}^{N}\sum_{k=1}^{K}\mu_{n,k}\left(Q_k\left[n\right] - a_k[n]\xi\right) + \sum_{k=1}^{K}\nu_k\left(E_k - \theta\right)\\
&= \left(1 - \sum_{k=1}^{K}\nu_k\right)\theta + \sum_{k=1}^{K}\nu_k\tilde{E}_k\\
&+ \sum_{n=1}^{N}\sum_{k=1}^{K}\left[\mu_{n,k}\left(Q_k\left[n\right] - a_k[n]\xi\right) + \delta\nu_k a_k\left[n\right]Q_k\left[n\right]\right]
\end{aligned} \tag{15}$$

where the Lagrangian multipliers ν_k and μ_n are corresponding to the constraint (12) and (13) of problem $\left(\bar{\mathrm{P}}1.1\right)$, respectively. Accordingly, the dual function for problem $\left(\bar{\mathrm{P}}1.1\right)$ can be written as

$$g\left(\nu_k, \mu_{n,k}\right) = \begin{cases} \max\limits_{a_k[n],\theta} \mathcal{L}\left(a_k\left[n\right], \theta, \nu_k, \mu_{n,k}\right) \\ \text{s.t.} \quad 0 \le a_k\left[n\right] \le 1, \forall k, n \end{cases} \tag{16}$$

Next, we will prove $1 - \sum\limits_{k=1}^{K}\nu_k = 0$ with the method of reduction to absurdity. Suppose that $1 - \sum\limits_{k=1}^{K}\nu_k < 0$ (or $1 - \sum\limits_{k=1}^{K}\nu_k > 0$), and let $\theta \to -\infty$ (or $\theta \to \infty$) from (16). Then, the dual function $g\left(\nu_k, \mu_{n,k}\right)$ will tend to infinity, which is contradictory with the boundedness of $g\left(\nu_k, \mu_{n,k}\right)$. Thus, $1 - \sum\limits_{k=1}^{K}\nu_k = 0$ should be satisfied.

With the given dual variables ν_k and $\mu_{n,k}$, the dual function $g\left(\nu_k, \mu_{n,k}\right)$ can be solved to obtain the optimal solutions $a_k[n]$ and θ. Since $1 - \sum\limits_{k=1}^{K}\nu_k = 0$, the optimal value of θ can be chosen with any real value. Based on this, it is clear that if $\left(\delta\nu_k Q_k\left[n\right] - \xi\mu_{n,k}\right) \ge 0$, $a_k[n] = 1$ will make $\left(\delta\nu_k Q_k\left[n\right] - \xi\mu_{n,k}\right)a_k\left[n\right]$ maximized, otherwise, $a_k[n] = 0$. This completes the proof. ■

3.2 UAV Trajectory Optimization

In this subsection, we consider the second subproblem of (P1), namely optimizing UAV trajectory Q with a given wake-up scheduling scheme. As such, the UAV trajectory optimization subproblem can be formulated as

$$
\begin{aligned}
\text{(P1.2)}:\ & \max_{\{Q,\theta\}} \ \eta \\
\text{s.t.}\ & E_k \geq \eta, \quad \forall k, && (17)\\
& Q_k[n] \geq a_k[n]\xi, \ \forall k, n, && (18)\\
& \|\mathbf{q}[n+1]-\mathbf{q}[n]\|^2 \leq (V_{\max}\delta)^2, \\
& \qquad\qquad n = 1, \ldots, N-1, && (19)\\
& \mathbf{q}[1] = \mathbf{q}_0, && (20)\\
& \mathbf{q}[N] = \mathbf{q}_{\mathrm{F}}. && (21)
\end{aligned}
$$

It is worth stressing that the problem (P1.2) is still non-convex owing to the common term $\|\mathbf{q}[n]-\mathbf{w}_k[n]\|^2$ in constraints (17) and (18), which is challenging to find its optimal solutions. However, since $Q_k[n]$ in (4) is convex with respect to (w.r.t.) $\|\mathbf{q}[n]-\mathbf{w}_k[n]\|^2$. Thus, based on successive convex optimization techniques, we can obtain an approximate solution to problem (P1.2). Specifically, the left-hand side (LHF) of (17) and (18) are replaced by their own lower bounds via successively optimizing the incremental of UAV's trajectory at each iteration.

To proceed, let $Q_l = \{\mathbf{q}_l[n], \forall n\}$ denote the UAV's trajectory at l-th iteration, and $\{\triangle\mathbf{q}_l[n]\}_{n=2}^{N-1}$ denote the UAV's displacement. Then, the UAV's trajectory at $(l+1)$-th iteration at time slot n can be expressed as

$$
\mathbf{q}_{l+1}[n] = \mathbf{q}_l[n] + \triangle\mathbf{q}_l[n], \ n = 2, \ldots N-1, \tag{22}
$$

With the resulting trajectory after the l-th iteration, the corresponding harvested power by node k at l-th iteration over time slot n can be written as $Q_{k,l}[n] = \frac{\eta_0 P\beta_0}{\|\mathbf{q}_l[n]-\mathbf{w}_k\|^2+H^2}$. Then, we have the following Lemma.

Lemma 1. *For any given UAV trajectory incremental* $\{\triangle\mathbf{q}_l[n]\}_{n=2}^{N-1}$, *the following inequality holds*

$$
Q_{k,l+1}[n] \geq Q_{k,l+1}^{\mathrm{lb}}[n] = \frac{\eta_k P\beta_0}{d_{k,l}^2[n]} - \frac{\eta_k P\beta_0}{d_{k,l}^4[n]}\Delta, \tag{23}
$$

where $d_{k,l}[n] = \sqrt{\|\mathbf{q}_l[n]-\mathbf{w}_k\|^2+H^2}$, $\Delta = \|\triangle\mathbf{q}_l[n]\|^2 + 2(\triangle\mathbf{q}_l[n]-\mathbf{w}_k)^{\mathrm{T}}\mathbf{q}_l[n]$, $n = 2, \ldots, N-1$.

Proof. Define a function $f(x) = \frac{a}{b+x}$ with constants $a > 0$ and $b > 0$. Clearly, $f(x)$ is convex w.r.t. $x \in (-b, \infty]$. Recall that any convex function is globally lower-bounded by its first-order Taylor expansion at any feasible point [2], i.e., $f(x) \geq f(x_0) + f'(x_0)(x-x_0)$. By setting $x_0 = 0$, we have

$$
\frac{a}{b+x} \geq \frac{a}{b} - \frac{a}{b^2}x, \tag{24}
$$

Hence, the harvested power $Q_{k,l+1}[n]$ can be expressed as

$$\begin{aligned} Q_{k,l+1}[n] &= \frac{\eta_k P \beta_0}{\left\|\mathbf{q}_{l+1}[n] - \mathbf{w}_k\right\|^2 + H^2} \\ &= \frac{\eta_k P \beta_0}{d_{k,l}^2[n] + \varDelta} \\ &\geq \frac{\eta_k P \beta_0}{d_{k,l}^2[n]} - \frac{\eta_k P \beta_0}{d_{k,l}^4[n]} \varDelta = Q_{k,l+1}^{\mathrm{lb}}, \end{aligned} \tag{25}$$

where $d_{k,l}[n] = \sqrt{\left\|\mathbf{q}_l[n] - \mathbf{w}_k\right\|^2 + H^2}$, $\varDelta = \left\|\triangle\mathbf{q}_l[n]\right\|^2 + 2(\triangle\mathbf{q}_l[n] - \mathbf{w}_k)^{\mathrm{T}}\mathbf{q}_l[n]$ with $n = 2, \ldots, N-1$. This completes the proof. ■

Lemma 1 tells us that for given UAV trajectory Q_l and incremental $\{\triangle\mathbf{q}_l[n]\}_{n=2}^{N-1}$, the new iterated energy $E_{k,l+1}$ is lower-bounded by $E_{k,l+1}^{\mathrm{lb}}$, which is concave w.r.t. $\{\triangle\mathbf{q}_l[n]\}_{n=2}^{N-1}$. Then, we have

$$E_{k,l+1}^{\mathrm{lb}} = \delta \sum_{n=1}^{N} a_k[n]\, Q_{k,l+1}^{\mathrm{lb}}[n] + \tilde{E}_k. \tag{26}$$

By defining $\eta_{l+1}^{\mathrm{lb}}(Q_{l+1}, A_{l+1}) = \min\limits_{\forall k}\ E_{k,l+1}^{\mathrm{lb}}$, problem (P1.2) can be reformulated as follows

$$\left(\bar{\mathrm{P}}1.2\right): \max_{\left\{\{\triangle\mathbf{q}_l[n]\}_{n=2}^{N-1}, \eta_{l+1}^{\mathrm{lb}}\right\}} \eta_{l+1}^{\mathrm{lb}}$$

$$\text{s.t.} \quad E_{k,l+1}^{\mathrm{lb}} \geq \eta_{l+1}^{\mathrm{lb}}, \quad \forall k, \tag{27}$$

$$Q_{k,l+1}^{\mathrm{lb}}[n] \geq a_k[n]\xi, \quad \forall k, n, \tag{28}$$

$$\left\|\mathbf{q}_l[n+1] + \triangle\mathbf{q}_l[n+1] - \mathbf{q}_l[n] - \triangle\mathbf{q}_l[n]\right\|^2 \leq (V_{\max}\delta)^2, n = 2, \ldots, N-1, \tag{29}$$

$$\left\|\mathbf{q}_l[2] + \triangle\mathbf{q}_l[2] - \mathbf{q}[1]\right\|^2 \leq (V_{\max}\delta)^2, \tag{30}$$

$$\left\|\mathbf{q}[N] - \mathbf{q}_l[N-1] - \triangle\mathbf{q}_l[N-1]\right\|^2 \leq (V_{\max}\delta)^2,$$

$$\mathbf{q}[1] = \mathbf{q}_0, \tag{31}$$

$$\mathbf{q}[N] = \mathbf{q}_{\mathrm{F}} \tag{32}$$

Kindly note that the LHS of constraint (27) are concave w.r.t. $\{\triangle\mathbf{q}_l[n]\}_{n=2}^{N-1}$. Therefore, the problem $\left(\bar{\mathrm{P}}1.2\right)$ is convex. As a result, we can resort to using standard convex technique to solve it, and the problem (P1.2) can be approximately solved by successively updating $\mathbf{q}_{l+1}[n]$ based on the optimal solution to $\left(\bar{\mathrm{P}}1.2\right)$, which is summarized in Algorithm 1. Furthermore the optimal value of problem (P1.2) is lower bounded by the optimal solution in Algorithm 1.

Algorithm 1. Successive Trajectory Optimization with Fixed Wake Up Scheduling.

1: **Initialize** $\{\mathbf{q}_0[n]\}_{n=2}^{N-1}$, $\mathbf{q}[1] = \mathbf{q}_0$, $\mathbf{q}[N] = \mathbf{q}_{\mathrm{F}}$, $l \leftarrow 0$, the tolerance $\varepsilon > 0$.
2: **Repeat**
3: Obtain optimal solution $\{\triangle\mathbf{q}_l[n]\}_{n=2}^{N-1}$ of $(\bar{\mathrm{P}}1.2)$.
4: Update UAV's trajectory $\mathbf{q}_{l+1}[n] \leftarrow \mathbf{q}_l[n] + \triangle\mathbf{q}_l[n]$.
5: $l \leftarrow l + 1$.
6: **Until** The fractional increase of the objective value of $(\bar{\mathrm{P}}1.2)$ is less than tolerance ε.

3.3 Joint Wake-Up Scheduling and UAV Trajectory Optimization

In this subsection, with the solutions to problem (P1.1) and $(\bar{\mathrm{P}}1.2)$, we propose an iterative algorithm for jointly optimizing wake-up scheduling and UAV trajectory, which is summarized in Algorithm 2. Note that since the subproblem (P1.2) for UAV trajectory optimization cannot be optimally solved by Algorithm 1, thus the optimality cannot be directly declared for Algorithm 2.

Algorithm 2. Block Coordinate Descent Method for Problem (P1).

1: **Initialize** the UAV's trajectory as $\{\mathbf{q}_0[n]\}_{n=2}^{N-1}$, $\mathbf{q}[1] = \mathbf{q}_0$, $\mathbf{q}[N] = \mathbf{q}_{\mathrm{F}}$, and $l \leftarrow 0$ as well as tolerance $\varepsilon > 0$.
2: **repeat**.
3: Obtain the optimal wake-up scheduling criteria $\{a_{k,l}[n]\}$,$\forall n = 1, \ldots, N$ and $\forall k = 1, \ldots, K$ to problem $(\bar{\mathrm{P}}1.1)$.
4: Fix the wake-up scheduling criteria $\{a_{k,l}[n]\}$ obtained from step 3, then obtain the optimal UAV trajectory $\{\mathbf{q}_{l+1}[n]\}$ using Algorithm 1.
5: Update $l \leftarrow l + 1$.
6: **until** the fractional increase of the objective value of (P1) is less than tolerance ε.

3.4 Convergence Proof for Proposed Algorithm

In this subsection, the convergence properties of the proposed Algorithms 1 and 2 will be analyzed, respectively. First, for the given trajectory Q_l, the optimal solution to problem (P1.1) can be denoted as A_{l+1}. Thus, we have

$$\theta(Q_l, A_l) \leq \theta(Q_l, A_{l+1}). \tag{33}$$

At each iteration in Algorithm 1, the objective function η_{l+1}^{lb} is non-decreasing over l as follows

$$\eta_l^{\mathrm{lb}}(Q_l, A_{l+1}) \leq \eta_{l+1}^{\mathrm{lb}}(Q_{l+1}, A_{l+1}). \tag{34}$$

Based on the fact that problem (P1.2) is upper-bounded by a finite value, Algorithm 1 is guaranteed to converge. Due to the fact that $\theta\left(Q_l, A_{l+1}\right) = \eta_l^{\mathrm{lb}}\left(Q_l, A_{l+1}\right)$, $\eta_{l+1}^{\mathrm{lb}}\left(Q_{l+1}, A_{l+1}\right) \leq \eta_{l+1}\left(Q_{l+1}, A_{l+1}\right)$ and $\eta_{l+1}\left(Q_{l+1}, A_{l+1}\right) = \theta_{l+1}\left(Q_{l+1}, A_{l+1}\right)$, it is readily to declare that $\theta\left(Q_l, A_l\right) \leq \theta_{l+1}\left(Q_{l+1}, A_{l+1}\right)$, which indicates that Algorithm 2 is non-decreasing over each iteration l. Furthermore, since the objective value of (P1) is upper-bounded by a finite value, Algorithm 2 is also guaranteed to converge.

4 Numerical Results

In this section, numerical results are provided to evaluate the performance of our proposed UAV-aided WPT scheme. In our system, we consider $K = 4$ SNs randomly distributed within a geographic area of size $100 \times 100\,\mathrm{m}^2$. The involved parameters are set as follows: $V_{\max} = 10\,\mathrm{m/s}$, $H = 10\,\mathrm{m}$, $P = 10\,\mathrm{W}$, $\beta_0 = 1$, $\xi = 10^{-4}$. Furthermore, we choose the time slot duration as $\delta = 0.3\,\mathrm{s}$. Without loss of generality, the energy harvesting efficiency coefficient is same, i.e., $\eta_k = \eta_0 = 0.7, \forall k$. Moreover, the residual energy at each SN follows Poisson distribution with same expectation, i.e., $\lambda_k = \lambda = 0.4\,\mathrm{J}$.

We first consider the case $\tilde{E}_k = 0, \forall k$, which implies that all the SNs have no energy retained at initialization. Figure 2 plots the UAV trajectory with different horizon time T. Without loss of generality, the UAV's initial and final locations are fixed to $\mathbf{q}_0 = (-100, 0)^{\mathrm{T}}$ and $\mathbf{q}_{\mathrm{F}} = (100, 0)^{\mathrm{T}}$, respectively. It can be observed from Fig. 2 that as T increases, UAV moves closer to the ground nodes. This is attributed to the fact that the longer flying time allowed, the more distance

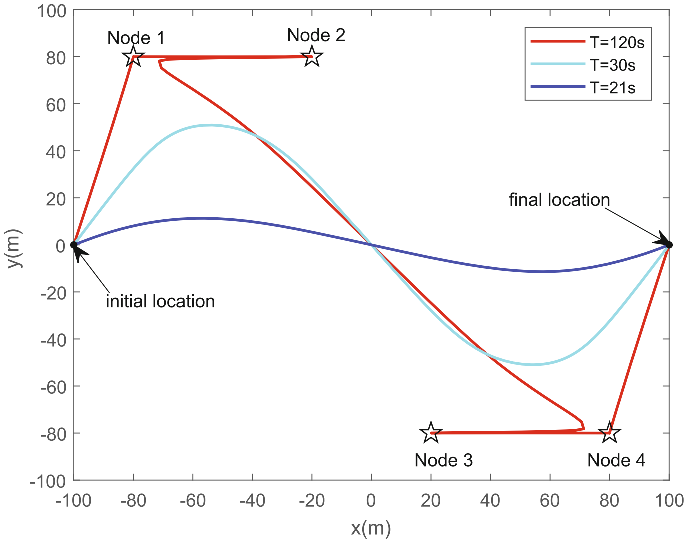

Fig. 2. UAV trajectory with different horizon time T.

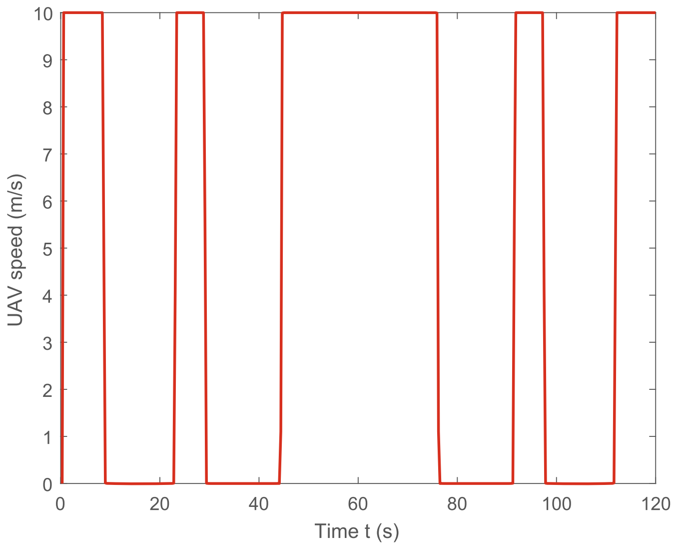

Fig. 3. UAV speed over time instant n at $T = 120\,\text{s}$.

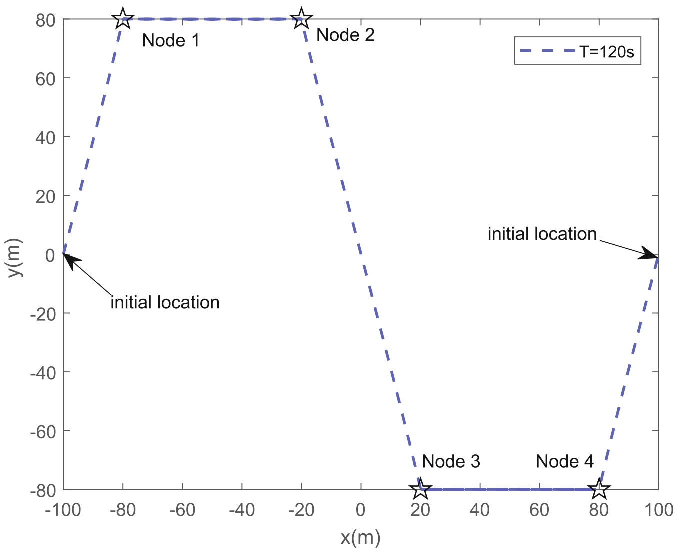

Fig. 4. UAV trajectory with different level of residual energy at each node.

can be traveled. Figure 3 depicts the UAV variation-speed corresponding to UAV trajectory in Fig. 2 at $T = 120\,\text{s}$. It can be found that the equal dwell time is allocated to each node as horizon time T is sufficiently large.

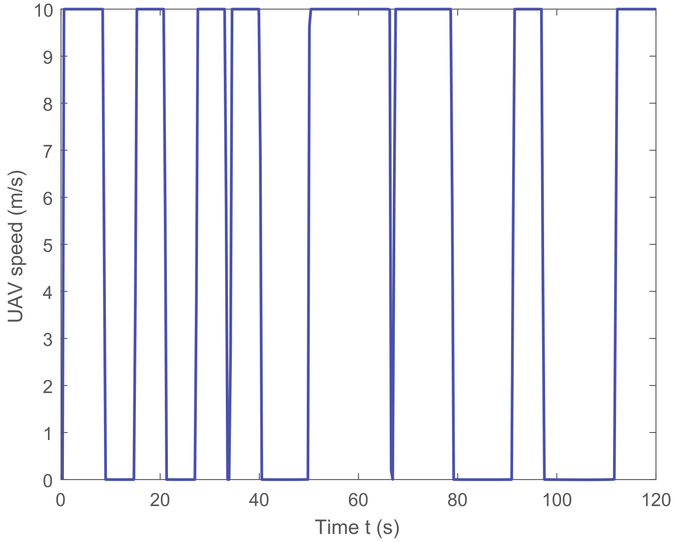

Fig. 5. UAV speed corresponding to UAV trajectory as shown in Fig. 4.

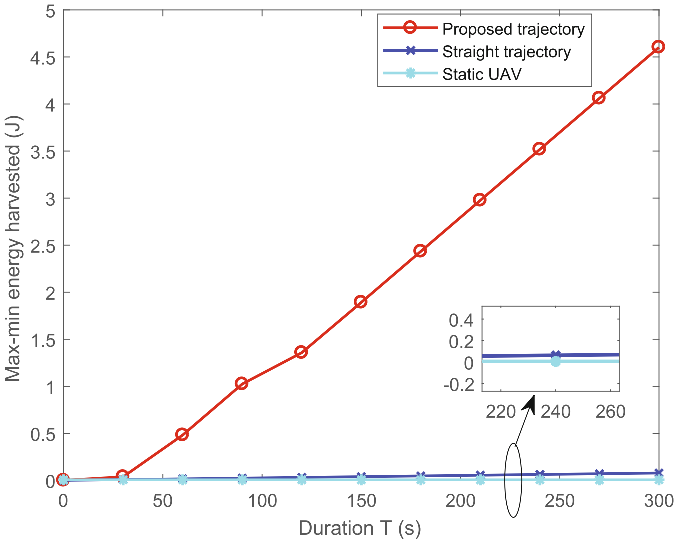

Fig. 6. Max-min energy harvested with different schemes.

Next, we consider that each SN has different levels of residual energy. The residual energy are respectively given by $\tilde{E}_1 = 0.8\,\mathrm{J}$, $\tilde{E}_2 = 0.2\,\mathrm{J}$, $\tilde{E}_3 = 0.6\,\mathrm{J}$ and $\tilde{E}_4 = 0.3\,\mathrm{J}$, which obtained by random realization with mean 0.4 J. It can be seen from Figs. 4 and 5 that UAV moves directly to node k with shortest distance, and different dwell time is allocated to each SN. Specifically, UAV spends a large mount of time to hover above the node which has less residual energy, and less time is allocated to hover above the node which has larger residual energy. This is attributed to the fact that the SN with less energy needs more time to be served by UAV.

At last, we compare our proposed scheme with static UAV scheme and traditional straight trajectory scheme for max-min energy harvested as shown in Fig. 6. It is reasonable to assume that the location of static UAV is located at the geometric center $\mathbf{q}_{\text{static}} = (0,0)^{\text{T}} \in \mathbb{R}^{2\times 1}$ and the straight trajectory is set as $\mathbf{q}[n] = \mathbf{q}_1 + \frac{\mathbf{q}_N - \mathbf{q}_1}{N-1}n, n = 0, \ldots, N-1$. To process, the wake-up scheduling is optimized for both static UAV and straight trajectory schemes. One can find that the proposed scheme outperforms the two benchmark schemes. Furthermore, the performance gain is more remarkable as T increases. This is because UAV can move closer to or hover above SNs for power charge with better channel condition. As a result, the max-min total achieved energy is improved.

5 Conclusion

In this paper, we have investigated a novel UAV-aided WPT system, where the UAV charges the SNs according to the fairness criteria by jointly optimizing the UAV's trajectory and SNs' scheduling scheme with the flying constraints. The established problem is a non-convex mixed integer problem, which is difficult to tackle. Thus, we propose an efficient iterative algorithm by jointly optimizing wake-up scheduling and UAV trajectory with successive convex optimization techniques. Simulation results provide two significant insights. First, our proposed scheme has achieved significant performance gain over two benchmarks, which indicates that the UAV trajectory has significantly impacted on the WPT system. Second, for the same levels of residual energy at SNs, the equal dwell time is allocated to each node as horizon time T is sufficiently large. Furthermore, for different levels of residual energy at SNs, UAV spends more time to hover above the energy-less SNs, which indicates that the UAV prefers to serve the energy-drained SNs.

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