Throughput Maximization for UAV-Enabled Wireless Powered Communication Networks

(Invited Paper)

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Abstract—This paper studies an unmanned aerial vehicle (UAV)-enabled wireless powered communication network (WPCN), in which a UAV is dispatched as a mobile access point (AP) to serve a set of ground users periodically. The UAV employs the radio frequency (RF) wireless power transfer (WPT) to charge the users in the downlink, and the users use the harvested RF energy to send independent information to the UAV in the uplink. Unlike the conventional WPCN with fixed APs, the UAV-enabled WPCN can exploit the mobility of the UAV via periodic trajectory design, jointly with the transmission resource allocation optimization, to improve the system performance. In particular, we aim to maximize the uplink common (minimum) throughput among all ground users over a finite UAV’s flight period, subject to its maximum speed constraint and the users’ energy neutrality constraints. The resulting problem is non-convex and thus difficult to be solved optimally. To tackle this challenge, we first consider an ideal case without the maximum UAV speed constraint, and obtain the optimal solution to the relaxed problem. The optimal solution shows that the UAV should successively hover above a finite number of ground locations for downlink WPT, as well as above each of the ground users for uplink communication. Next, based on the above multi-location-hovering solution, we propose a successive hover-and-fly trajectory, jointly with the downlink and uplink power allocations, to find an efficient suboptimal solution to the problem with the maximum UAV speed constraint. Numerical results show that the proposed UAV-enabled WPCN achieves significant common throughput gain over the conventional WPCN with a fixed-location AP.

I. INTRODUCTION

Radio frequency (RF) wireless power transfer (WPT) has emerged as a promising solution to provide convenient and reliable energy supply to low-power wireless devices (WDs) for enabling future Internet-of-things (IoT) [1]. One important application of WPT in wireless communications is the so-called wireless powered communication network (WPCN), in which dedicated access points (APs) are deployed (usually at fixed locations) to charge a set of WDs via WPT in the downlink, and the WDs can use the harvested energy to send information back to the AP in the uplink [2].

The conventional WPCN with fixed APs faces several issues. First, due to the severe propagation loss of RF signals over distance, the end-to-end WPT efficiency is generally low when the distance from the AP to a WD becomes large. Furthermore, the conventional WPCN suffers from a so-called “doubly near-far” problem [2], i.e., far-apart WDs from the AP receive lower RF energy in the downlink WPT, but they need to use higher transmit power in the uplink communication or wireless information transfer (WIT) to achieve the same rate as nearby WDs. The doubly near-far problem leads to a severe user fairness issue among WDs when they are geographically distributed over a large area. In the literature, various approaches have been proposed to overcome this issue, including e.g., adaptive time and power allocation [2], multi-antenna beamforming [3]–[6], and user cooperation [7], [8]. Different from the above work that focused on enhancing the WPT/WIT performances with fixed APs, this paper proposes an alternative solution based on a new unmanned aerial vehicle (UAV)-enabled WPCN architecture with the UAV employed as a mobile AP.

UAVs have found abundant applications such as for cargo delivery, aerial surveillance, filming, and industrial IoT. Recently, UAV-enabled/aided wireless communications have attracted substantial research interests [9]. For example, UAVs can be utilized as mobile relays to help information exchange between far-apart ground users [10], or as mobile base stations (BSs) to help enhance the wireless coverage and/or increase the network capacity for ground mobiles [11]–[16]. Furthermore, UAV-enabled WPT has been proposed in [17], [18], in which UAVs are used as mobile energy transmitters to charge low-power WDs on the ground. By exploiting its fully controllable mobility, the UAV can properly adjust locations over time (a.k.a. trajectory) to reduce the distances with target ground users, thus improving the efficiency for both WPT and WIT.

Motivated by the UAV-enabled wireless communications as well as WPT, this paper pursues a unified study on both of them in a UAV-enabled WPCN as shown in Fig. 1.
a UAV following a periodic trajectory is dispatched as a mobile AP to charge a set of ground users in the downlink via WPT, and the users use the harvested RF energy to send independent information to the UAV in the uplink. We investigate how to optimally exploit the UAV mobility via trajectory design, jointly with the transmission resource allocation, to maximize the WPCN throughput. To this end, we maximize the uplink common (minimum) throughput among all ground users over a given UAV’s flight period, by jointly optimizing the UAV’s trajectory, as well as the UAV’s downlink power allocation for WPT and the users’ uplink power allocation for WIT. However, due to the complex objective function in terms of coupled UAV trajectory and power allocation, the above problem is non-convex and thus difficult to be solved optimally.

To tackle this difficulty, we first consider a relaxed problem without the UAV’s maximum speed constraint. We show that strong duality holds between this problem and its Lagrange dual problem, and thus it can be solved optimally via the Lagrange dual method. The optimal solution shows that the UAV should successively hover over a finite number of ground locations for downlink WPT, as well as above each of the ground users for uplink WIT, with the optimal hovering time and power allocation for each location. Next, we address the original problem with the maximum UAV speed constraint considered. Based on the multi-location-hovering solution to the above relaxed problem, we propose a successive hover-and-fly trajectory design, jointly with the downlink and uplink power allocations, to find an efficient suboptimal solution. The proposed solution is also shown to be asymptotically optimal as the UAV flight period becomes infinitely large. Finally, we present numerical results to validate the performance of our proposed UAV-enabled WPCN. It is shown that the joint trajectory and transmission resource allocation design significantly improves the uplink common throughput, as compared to the conventional WPCN with the AP at a fixed location.

II. System Model and Problem Formulation

As shown in Fig. 1, we consider a UAV-enabled WPCN, in which a UAV is dispatched to periodically charge a set of $K$ ground users via WPT in the downlink, and each user $k \in K = \{1, \ldots, K\}$ uses its harvested energy to send independent information back to the UAV in the uplink. Suppose that each user $k \in K$ is at a fixed location on the ground, which is denoted by $(x_k, y_k, 0)$ in a three-dimensional (3D) Cartesian coordinate system, where $w_k = (x_k, y_k)$ is defined as the horizontal coordinate of user $k$. The users’ locations are assumed to be a-priori known by the UAV for its trajectory design and transmission resource allocation.

We focus on a particular flight period of the UAV, denoted by $T = (0, T]$ with finite duration $T$ in second (s), in which the UAV flies horizontally at a fixed altitude $H > 0$ in meter (m). At any given time instant $t \in T$, let $q(t) = (x(t), y(t))$ denote the location of the UAV projected on the horizontal ground plane. Accordingly, the distance from the UAV to user $k$ is given by

$$d_k(q(t)) = \sqrt{\|q(t) - w_k\|^2 + H^2},$$

where $\| \cdot \|$ denotes the Euclidean norm of a vector. By denoting the maximum UAV speed as $V_{\text{max}}$ in m/s, we have

$$\sqrt{x^2(t) + y^2(t)} \leq V_{\text{max}}, \forall t \in T,$$

where $x(t)$ and $y(t)$ denote the time-derivatives of $x(t)$ and $y(t)$, respectively. Note that we assume the UAV can freely choose its initial location $q(0)$ and final location $q(T)$ for performance optimization.

We consider that the wireless channels between the UAV and the $K$ ground users are dominated by line-of-sight (LoS) links. In this case, the free-space path loss model can be practically assumed, similarly as in [10], [17]. Accordingly, the channel power gain between the UAV and user $k$ at time instant $t \in T$ is given by

$$h_k(q(t)) = \beta_0 d_k^{-2}(q(t)) = \frac{\beta_0}{\|q(t) - w_k\|^2 + H^2}, \forall k \in K,$$

where $\beta_0$ denotes the channel power gain at a reference distance of $d_0 = 1$ m.

We consider a time-division multiple access (TDMA) protocol, in which the downlink WPT and uplink WIT to/from different ground users are implemented in the same frequency band but over orthogonal time instants. At any time instant $t \in T$, we use the indicators $p_k(t) \in \{0, 1\}, \forall k \in \{0\} \cup K$, to denote the transmission mode in the system. We use $p_0(t) = 1$ and $p_k(t) = 0, \forall k \in K$, to indicate the downlink WPT mode, in which the UAV transmits to charge the $K$ users simultaneously; while we use $p_0(t) = 1, k \in K$, and $p_j = 0, \forall j \in \{0\} \cup K, j \neq k$, to represent the uplink WIT mode for user $k$, in which user $k$ sends its information to the UAV using its harvested energy. Due to TDMA, it follows that

$$\sum_{k=0}^{K} p_k(t) \leq 1, \forall t \in T.$$

First, consider the downlink WPT mode at time instant $t \in T$, in which $p_0(t) = 1$, and $p_k(t) = 0, \forall k \in K$. Let $P(t)$ denote the transmit power of the UAV. Accordingly, the harvested power at each user $k \in K$ is

$$E_k(p_0(t), q(t), P(t)) = \eta p_0(t) P(t) h_k(q(t))$$

where $0 < \eta \leq 1$ denotes the RF-to-direct current (DC) energy conversion efficiency at the energy harvester of each user. Therefore, the total harvested energy at user $k$ over the whole period of duration $T$ is given as

$$\dot{E}_k\{p_0(t), q(t), P(t)\} = \int_{0}^{T} E_k(p_0(t), q(t), P(t))dt.$$

Next, consider the WIT mode for user $k \in K$ at time instant $t \in T$ with $p_k(t) = 1$, and $p_j(t) = 0, \forall j \in \{0\} \cup K, j \neq k$. Let $Q_k(t)$ denote the transmit power of user $k$ for the uplink WIT to the UAV. Accordingly, the achievable data rate from user $k$ to the UAV in bits/second/Hertz (bps/Hz) is given by

$$r_k(p_k(t), q(t), Q_k(t)) = p_k(t) \log_2 \left( 1 + \frac{Q_k(t) h_k(q(t))}{\sigma^2} \right)$$

$$= p_k(t) \log_2 \left( 1 + \frac{Q_k(t)\gamma}{\|q(t) - w_k\|^2 + H^2} \right),$$

where $\sigma^2$ denotes the noise power at the information receiver of the UAV, and $\gamma \triangleq \beta_0/\sigma^2$ is the reference signal-to-noise ratio.
ratio (SNR).

Therefore, the average achievable rate of user \( k \) over each period is given by
\[
R_k(\{ \rho_k(t), q(t), Q_k(t) \}) = \frac{1}{T} \int_0^T r_k(\rho_k(t), q(t), Q_k(t)) dt.
\] (7)

Note that for the purpose of exposition, we consider that the energy consumption of each ground user is mainly due to the transmit power for its uplink WIT. In this case, the total energy consumption at user \( k \in K \) is
\[
\hat{Q}_k(\{ \rho_k(t), Q_k(t) \}) = \int_0^T \rho_k(t) Q_k(t) dt.
\] (8)

In order to achieve the self-sustainable operation of ground users, each user \( k \)'s energy consumption for uplink WIT (i.e., \( \hat{Q}_k(\{ \rho_k(t), Q_k(t) \}) \) in (8)) cannot exceed that harvested from the downlink WPT (i.e., \( E_k(\{ \rho_0(t), q(t), P(t) \}) \) in (5)) in each period. As a result, we have the following energy neutrality constraints for each of the \( K \) users.
\[
\int_0^T \rho_k(t) Q_k(t) dt \leq \int_0^T E_k(\rho_0(t), q(t), P(t)) dt, \forall k \in K.
\] (9)

In this work, our objective is to maximize the uplink common throughput among all users (i.e., \( \min_{k \in K} \hat{R}_k(\{ \rho_k(t), q(t), Q_k(t) \}) \)) subject to the maximum UAV speed constraint in (2) and the \( K \) users’ energy neutrality constraints in (9). The decision variables include the UAV trajectory \( \{ q(t) \} \), the transmission mode \( \{ \rho_k(t) \} \), the transmit power \( \{ P(t) \} \) for downlink WPT, and \( \{ Q_k(t) \} \) for uplink WIT. Specifically, the problem is formulated as
\[
\text{(P1)}: \max_{\{ \rho_k(t), q(t), Q_k(t) \}} \min_{k \in K} R_k(\{ \rho_k(t), q(t), Q_k(t) \})
\] s.t. \( 0 \leq P(t) \leq P_{\text{peak}}, \forall t \in T \)
\[
Q_k(t) \geq 0, \forall k \in K, t \in T
\] (10)
\[
\rho_k(t) \in \{ 0, 1 \}, \forall k \in \{ 0 \} \cup K, t \in T
\] (11)
\[
\sum_{k=0}^{K} \rho_k(t) = 1, \forall t \in T
\] (12)
\[
\text{(2) and (9)},
\]
where \( P_{\text{peak}} \) in (10) denotes the peak transmit power at the UAV for downlink WPT.

It is observed that for problem (P1), the objective function and the constraints (9) and (12) are all non-convex, due to the coupling of variables \( \rho_k(t), q(t), P(t) \) (or \( Q_k(t) \)), as well as the binary constraints on \( \rho_k(t) \)'s. Therefore, (P1) is a non-convex optimization problem. Furthermore, (P1) contains an infinite number of optimization variables over continuous time. For these reasons, problem (P1) is difficult to be solved optimally. To tackle this difficulty, in Section III we first optimally solve the following relaxed problem by ignoring the maximum UAV speed constraint in (2).
\[
\text{(P2)}: \max_{\{ \rho_k(t), q(t), Q_k(t) \}} \min_{k \in K} R_k(\{ \rho_k(t), q(t), Q_k(t) \})
\] s.t. \( 9, 10, 11, 12, \) and (13).

Then in Section IV, we propose an efficient suboptimal solution to the original problem (P1) based on the optimal solution obtained for (P2). Note that due to the space limitation, in this paper we have omitted all the proofs, which will be provided in the journal version of this work.

III. OPTIMAL SOLUTION TO PROBLEM (P2)

By introducing an auxiliary variable \( R \), problem (P2) can be equivalently expressed as
\[
\text{(P2.1)}: \max_{\{ \rho_k(t), P(t), \{ q(t), Q_k(t) \} \}} R
\] s.t. \( \frac{1}{T} \int_0^T r_k(\rho_k(t), q(t), Q_k(t)) dt \geq R, \forall k \in K \)
\[
(9), (10), (11), (12), \) and (13).

Although problem (P2.1) is still non-convex, one can easily show that it satisfies the so-called time-sharing condition in [19]. Therefore, the strong duality holds between (P2.1) and its Lagrange dual problem. As a result, we can optimally solve (P2.1) by using the Lagrange dual method.

Let \( \lambda_k \geq 0 \) and \( \mu_k \geq 0, \forall k \in K \), denote the dual variables associated with the \( k \)-th constraints in (14) and (9), respectively. For notational convenience, we define \( \lambda = [\lambda_1, \lambda_2, \ldots, \lambda_K] \) and \( \mu = [\mu_1, \mu_2, \ldots, \mu_K] \). The partial Lagrangian of (P2.1) is
\[
\mathcal{L}(\rho_k(t), P(t), Q_k(t), q(t)), R, \lambda, \mu)
\]
\[
= \left(1 - \frac{K}{K} \right) R + \sum_{k=1}^{K} \frac{K}{T} \int_0^T r_k(\rho_k(t), q(t), Q_k(t)) dt
\] + \[
\sum_{k=1}^{K} \mu_k \left( \int_0^T E_k(\rho_0(t), q(t), P(t)) dt - \int_0^T \rho_k(t) Q_k(t) dt \right).
\] (15)

The dual function of (P2.1) is
\[
\mathcal{g}(\lambda, \mu) = \max_{\{ q(t), Q_k(t), P(t), \rho_k(t) \}} \mathcal{L}(\rho_k(t), P(t), Q_k(t), q(t)), R, \lambda, \mu)
\] s.t. (10), (11), (12) and (13).
\] (16)

Lemma 3.1: In order for the dual function \( \mathcal{g}(\lambda, \mu) \) to be upper-bounded from above (i.e., \( \mathcal{g}(\lambda, \mu) < \infty \)), it must hold that \( \sum_{k=1}^{K} \lambda_k = 1 \).

As a result, the dual problem is given by
\[
\text{(D2.1)}: \min_{\lambda, \mu} \mathcal{g}(\lambda, \mu)
\] s.t. \( \sum_{k=1}^{K} \lambda_k = 1 \)
\[
\lambda_k \geq 0, \mu_k \geq 0, \forall k \in K.
\]

Let the set of \( \lambda \) and \( \mu \) specified by the constraints in (D2.1) be \( \mathcal{X} \). As strong duality holds between (P2.1) and (D2.1), we can solve (P2.1) by equivalently solving (D2.1). In the following, we first obtain \( \mathcal{g}(\lambda, \mu) \) by solving problem (16) under given \( (\lambda, \mu) \in \mathcal{X} \), and then find the optimal \( \lambda \) and \( \mu \) to minimize \( \mathcal{g}(\lambda, \mu) \).

1) Obtaining \( \mathcal{g}(\lambda, \mu) \) by Solving Problem (16) Under Given \( (\lambda, \mu) \in \mathcal{X} \):

First, consider problem (16) under any given \( (\lambda, \mu) \in \mathcal{X} \). It is evident that problem (16) can be decomposed into the following two subproblems.
\[
\max_{R} \left(1 - \sum_{k=1}^{K} \lambda_k\right) R.
\] (17)
\[
\begin{align*}
\max_{\{Q_k(t)\}, q(t), P(t), \{\rho_k(t)\}} & \sum_{k \in K} \rho_k(t) \varphi_k(q(t), Q_k(t), \lambda_k, \mu_k) \\
& + \rho_0(t) \phi(q(t), P(t), \mu_k) \\
\text{s.t.} & \quad 0 \leq P(t) \leq P_{\text{peak}}, \quad Q_k(t) \geq 0, \forall k \in K \\
& \quad \rho_k(t) \in \{0, 1\}, \forall k \in \{0\} \cup K, \sum_{k=0}^{K} \rho_k(t) = 1,
\end{align*}
\] (18)

Here, problem (18) consists of an infinite number of subproblems, each corresponding to one time instant \( t \).

Note that the optimal value of problem (17) is always zero since \( 1 - \sum_{k \in K} \lambda_k = 0 \). In this case, the optimal solution \( R^* \) to problem (17) can be chosen as any arbitrary real number. Therefore, we only need to focus on the subproblems in (18). As the subproblems in (18) are identical for different time instants \( t \)'s, we can drop the index \( t \) for notational convenience, and denote the optimal solution as \( \{Q_k^*, q^*, P^*, \rho_k^*\} \).

Notice that for problem (18), there are a total of \( K + 1 \) feasible choices for \( \{\rho_k\} \) due to the constraints in (19). In the following problem (18) by first obtaining the maximum objective value (and the corresponding optimal \( Q_k^*, q^*, P^* \) and \( \{\rho_k^*\} \)).

First, consider that \( \rho_0 = 1 \) and \( \rho_k = 0, \forall k \in K \). In this case, we have the optimal solution to (18) as \( P = P_{\text{peak}}, Q_k = 0, \forall k \in K, \) and \( q = q^* \), where \( q^* = \{q_{\omega}^*, P_{\text{peak}}, \{\mu_k^*\}\} \) corresponds to the set of optimal hovering locations for downlink WPT, with \( \Omega(\mu^*) \geq 1 \) denoting the number of optimal solutions to problem (20). Accordingly, the optimal value of problem (18) is given as \( \phi(\{q_{\omega}^*\}, P_{\text{peak}}, \{\mu_k^*\}) \).

Next, consider that \( \rho_k = 1 \) for any \( k \in K \) and \( \rho_0 = 0, \forall j \in \{0\} \cup K, j \neq k \). In this case, we have the optimal solution to (18) as \( P = 0, q = w_k, Q_k = Q_k(\lambda_k, \mu_k) \triangleq \left( \frac{\lambda_k}{P_{\text{peak}}} \right)^{1/2} - \frac{\mu_k^2}{\gamma}, \) and \( Q_j = 0, \forall j \in K, j \neq k \), where \( \gamma = \max(\lambda_k, 0) \). Accordingly, the optimal value is \( \varphi_k(w_k, Q_k(\lambda_k, \mu_k), \lambda_k, \mu_k) \).

By comparing the \( K + 1 \) optimal values, i.e., \( \phi(\{q_{\omega}^*\}, P_{\text{peak}}, \{\mu_k^*\}) \) and \( \varphi_k(w_k, Q_k(\lambda_k, \mu_k), \lambda_k, \mu_k) \), \( q^* \in \{q_{\omega}^*, \ldots, q_{\Omega(\mu^*)}^*\} \),

\[
\text{where} \quad q^* \text{ is non-unique when } \Omega(\mu^*) > 1.
\]

- Otherwise, the UAV operates in the uplink WIT mode for user \( k^* \), i.e.,

\[
\begin{align*}
\rho_0^* = 0, \rho_k^* = 1, \rho_j^* = 0, \forall j \in K, j \neq k, \\
P^* = 0, Q_k^* = Q_k(\lambda_k, \mu_k), \quad \forall j \in K, j \neq k, \\
q^* = w_k^*.
\end{align*}
\] (22)

Note that if any two of the \( K + 1 \) optimal values (i.e., \( \phi(\{q_{\omega}^*\}, P_{\text{peak}}, \{\mu_k^*\}) \) and \( \varphi_k(w_k, Q_k(\lambda_k, \mu_k), \lambda_k, \mu_k) \)) are equal, then the corresponding solutions in (21) and (22) are both optimal for problem (18).

2) Finding Optimal \( \Lambda \) and \( \mu \) to Solve (D2.1): Next, we search over \( (\Lambda, \mu) \) to minimize \( g(\Lambda, \mu) \) for solving (D2.1). Since the dual problem (D2.1) is always convex but in general non-differentiable, we can use subgradient based methods, such as the ellipsoid method [20], to obtain the optimal \( \Lambda \) and \( \mu \), denoted by \( \Lambda^{\text{opt}} \) and \( \mu^{\text{opt}} \). Note that for the objective function \( g(\Lambda, \mu) \) in (D2.1), the subgradient with respect to \( (\Lambda, \mu) \) is

\[
\begin{align*}
& \left[ T_{\text{SC}}(\rho_k^*; q^*, P^*), \ldots, T_{\text{SC}}(\rho_K^*; q^*, P^*) \right], \\
& \text{where} \quad R^* \equiv 0, \text{ is chosen for simplicity}.
\end{align*}
\]

3) Constructing Optimal Primal Solution to (P2.1): With \( \Lambda^{\text{opt}} \) and \( \mu^{\text{opt}} \) obtained, we proceed to construct the optimal primal solution to (P2.1), denoted by \( \{\rho_k^*(t), P_{\text{opt}}^*(t), Q_k^*(t), q^*(t)\} \) and \( R_{\text{opt}} \). To start with, we have the following proposition.

Proposition 3.2: At the optimal \( \Lambda^{\text{opt}} \) and \( \mu^{\text{opt}} \), it must hold that \( \phi(\{q_{\omega}^{\text{opt}}\}, P_{\text{peak}}, \{\mu_k^{\text{opt}}\}) = \varphi_k(w_k, Q_k(\lambda_k^{\text{opt}}, \mu_k^{\text{opt}}), \lambda_k^{\text{opt}}, \mu_k^{\text{opt}}), \forall k \in K, \omega \in \{1, \ldots, \Omega(\mu^{\text{opt}})\} \).

By combining Propositions 3.1 and 3.2, it implies that under the optimal dual solution \( \Lambda^{\text{opt}} \) and \( \mu^{\text{opt}} \) to (D2.1), problem (18) has a total number of \( \Omega(\mu^{\text{opt}}) + K \) non-unique optimal solutions. Among them, the \( \Omega(\mu^{\text{opt}}) \) optimal solutions are given in (21), and the other \( K \) solutions are given in (22) (each for one user \( k \)). In this case, we need to time-share among these non-unique optimal solutions to construct the optimal primal solution to (P2.1).

Specifically, note that the \( \Omega(\mu^{\text{opt}}) \) solutions in (21) correspond to \( \Omega(\mu^{\text{opt}}) \) hovering locations \( q_1^{(\mu^{\text{opt}})}, \ldots, q_{\Omega(\mu^{\text{opt}})}^{(\mu^{\text{opt}})} \) for downlink WPT, at which only the UAV transmits with \( P^* = P_{\text{peak}} \) and \( \rho_0^* = 1 \); on the other hand, the \( k \)-th solutions in (22), \( k \in K \), corresponds to that the UAV hovers above user \( k \) at location \( w_k \) for uplink WPT, at which user \( k \) transmits with \( Q_k^* = Q_k(\lambda_k^{\text{opt}}, \mu_k^{\text{opt}}) \) and \( \rho_k^* = 1 \). With time-sharing, let \( \tau_{\omega} \) and \( \varsigma_k \) denote the hovering duration at the location \( q_\omega^{(\mu^{\text{opt}})} \), \( \omega \in \{1, \ldots, \Omega(\mu^{\text{opt}})\} \) and \( w_k, k \in \{1, \ldots, K\} \), respectively. In this case, we can solve the following uplink common throughput maximization problem to obtain the optimal hovering durations \( \tau_{\omega} \)'s and \( \varsigma_k \)'s for time sharing.

\[
\begin{align*}
\max_{\{\varsigma_k \geq 0, \tau_{\omega} \geq 0\}} R
\end{align*}
\] (P2.2)
s.t. \( \frac{S_k}{T} \log_2 \left( 1 + \frac{Q^k(k, n) \rho_k(k, n)}{H^2} \right) \geq R_k, \forall k \in \mathcal{K} \)

\[ q_k Q^k(k, n) = \sum_{\omega=1}^{\Omega^k(n)} \tau_{\omega} \eta_{\text{peak}} \| \mathbf{w}_k \|^2 + H^2, \forall k \in \mathcal{K} \]

\[ \sum_{k=1}^{K} q_k + \sum_{\omega=1}^{\Omega} \tau_{\omega} = T. \]

Note that problem (P2.2) is a linear program, which can be solved by standard convex optimization techniques [20]. The optimal solution to (P2.2) is denoted as \( \{q_k^*, \tau_{\omega}^*\} \) and \( \hat{T} \). Accordingly, we can divide the whole period \( T \) into \( \Omega^k(n) + K \) sub-periods, where the first \( \Omega^k(n) \) sub-periods, denoted by \( \mathcal{T}_w = \{ \sum_{\omega=1}^{\Omega^k(n)} \tau_{\omega}, \sum_{\omega=1}^{\Omega^k(n)} \tau_{\omega} \}, \forall \omega \in \{1, \ldots, \Omega^k(n)\} \), are for downlink WPT, and the next \( K \) sub-periods, denoted by \( \mathcal{T}_{Q^k(n)+1} = \{ \sum_{\omega=1}^{\Omega^k(n)} \tau_{\omega} + \sum_{j=1}^{K} \tau_{j}, \sum_{\omega=1}^{\Omega^k(n)} \tau_{\omega} + \sum_{j=1}^{K} \tau_{j} \}, \forall k \in \mathcal{K} \), are for uplink WIT of the \( K \) users. As a result, we have the following proposition.

**Proposition 3.3:** The optimal solution to (P2.1) (and thus (P2)) is given as follows. During sub-period \( \omega \in \{1, \ldots, \Omega^k(n)\} \), the UAV hovers at the location \( q^k_{\text{opt}} \) for downlink WPT, with

\[ q^k_{\text{opt}}(t) = q^k_{\text{opt}}, P^k_{\text{opt}}(t) = 1, \rho^k_{\text{opt}}(t) = 0, \]

\[ \forall t \in \mathcal{T}_w, \omega \in \{1, \ldots, \Omega^k(n)\} \]  

During sub-period \( \Omega^k(n) + k, k \in \{1, \ldots, \Omega\} \), the UAV hovers above user \( k \) at \( w_k \), and user \( k \) sends information to the UAV in the uplink, with

\[ q^k_{\text{opt}}(t) = w_k, P^k_{\text{opt}}(t) = 1, \rho^k_{\text{opt}}(t) = Q^k_{\text{opt}}(t) = 0, \]

\[ \forall t \in \mathcal{T}_{Q^k(n)+k}, k \in \{1, \ldots, \Omega\} \]  

The optimal uplink common throughput is given as \( R^u = \hat{T} \) (with \( \hat{T} \) denoting the optimal solution obtained for (P2.2)).

**IV. PROPOSED SOLUTION TO PROBLEM (P1)***

This section considers problem (P1) with the maximum UAV speed constraint in (2). We first present a successive hover-and-fly trajectory based on the multi-location-hovering solution to the relaxed problem (P2) presented in the previous section, and then solve (P1) sub-optimally.

**A. Successive Hover-and-Fly Trajectory Design**

First, we propose a successive hover-and-fly trajectory design, in which the UAV sequentially visits the \( \Omega^k(n) + K \) optimal hovering locations that are obtained for (P2), i.e., \( q^k_1, \ldots, q^k_{\Omega^k(n)} \) for downlink WPT, and \( w_1, \ldots, w_K \) for uplink WIT. For notational convenience, we denote the \( \Omega^k(n) + K \) hovering locations as \( \{q^k_n\} \), where \( q^k_n = q^k_{\text{opt}} \), \( \forall k \in \{1, \ldots, \Omega\} \), and \( q^k_{\Omega^k(n)+k} = w_k, \forall k \in \{1, \ldots, K\} \). In order to maximize the time for efficient WPT and WIT, the UAV flies among these hovering locations by using the maximum speed \( V_{\text{max}} \), and the UAV aims to minimize the flying time by equivalently minimizing the travelling path among the \( \Omega^k(n) + K \) locations.

First, we obtain the travelling path to minimize the flying distance to visit all the \( \Omega^k(n) + K \) hovering locations. We define a set of binary variables \( f_j, k, j \in \{1, \ldots, \Omega^k(n) + K\} \), \( j \neq k \), where \( f_j, k = 1 \) or \( f_j, k = 0 \) indicates that the UAV flies or does not fly from the \( j \)-th hovering location \( q^k_{\text{opt}} \) to the \( k \)-th hovering location \( q^k_{\text{opt}} \). Hence, the travelling path minimization problem becomes determining \( \{f_j, k\} \) to minimize \( \sum_{j=1}^{\Omega^k(n)+K} \sum_{k=1, k \neq j}^{K} f_j, k d_j, k \), provided that each of the \( \Omega^k(n) + K \) locations is visited once, where \( d_j, k = \|q^k_{\text{opt}} - q^k_{\text{opt}}\| \) denotes the distance between \( q^k_{\text{opt}} \) and \( q^k_{\text{opt}} \). Note that as shown in [17], the flying distance minimization can be equivalently solved by a well-known travelling salesman problem (TSP), for which the details are omitted here for brevity. In this case, we use the permutation \( \kappa(\cdot) \) over the set \( \{1, \ldots, \Omega^k(n) + K\} \) to denote the obtained travelling path, where the \( \kappa(1) \)-th hovering location is first visited, followed by the \( \kappa(2) \)-th, the \( \kappa(3) \)-th, etc., until the last \( \kappa(K) + \Omega^k(n) \)-th hovering location is visited. We denote the total travelling distance and duration as \( D_{\text{fly}} = \sum_{j=1}^{\Omega^k(n)+K} d_{\kappa(j), \kappa(j+1)} \) and \( \hat{T}_{\text{fly}} = \sum_{j=1}^{\Omega^k(n)+K-1} d_{\kappa(j), \kappa(j+1)} \), respectively, \( \forall i \in \{1, \ldots, K, \Omega^k(n) + K - 1\} \). Hence, the travelling distance and duration are given as \( D_{\text{fly}} = \sum_{j=1}^{\Omega^k(n)+K} d_{\kappa(j), \kappa(j+1)} \) and \( \hat{T}_{\text{fly}} = \sum_{j=1}^{\Omega^k(n)+K-1} d_{\kappa(j), \kappa(j+1)} \). We denote the obtained flying trajectory as \( \{q(t)\}_{t=0}^{T_{\text{fly}}} \).

To obtain the complete hover-and-fly trajectory, we still need to determine the hovering durations at the \( \Omega^k(n) + K \) hovering locations. Let \( \tau_{\omega} \) denote the time duration for the UAV to hover at the location \( q^k_{\text{opt}} = q^k_{\text{opt}} \) for WPT, \( \omega \in \{1, \ldots, \Omega^k(n)\} \), and \( \tau_{\omega} \) denote the time duration for the UAV to hover above user \( k \) at \( q^k_{\text{opt}} = w_k \) for WIT, \( k \in \{1, \ldots, K\} \). Furthermore, we define

\[ \zeta_k \triangleq \left\{ \begin{array}{ll}
\tau_{\kappa(k)}, & \text{if } \kappa(k) \in \{1, \ldots, \Omega\} \\
\frac{\zeta_{\kappa(k)}(n) - \zeta_{\kappa(k)}(n+1)}{2}, & \text{if } \kappa(k) \in \{\Omega^k(n) + 1, \ldots, \Omega^k(n) + K\}.
\end{array} \right. \]

Accordingly, we can divide the time duration into \( 2(\Omega^k(n) + K) - 1 \) sub-phases, denoted by \( \mathcal{T}_1, \mathcal{T}_2, \ldots, \mathcal{T}_{2(\Omega^k(n) + K) - 1} \), which are defined as

\[ \mathcal{T}_{2k-1} = \left( \sum_{j=1}^{k-1} (\zeta_{\kappa(j)} + T_{\text{fly}, i}), \sum_{j=1}^{k-1} (\zeta_{\kappa(j)} + T_{\text{fly}, i}) + \zeta_{\kappa(k)}(n) \right) \]

for odd sub-phases with \( k \in \{1, \ldots, \Omega^k(n) + K\} \), and

\[ \mathcal{T}_{2k} = \left( \sum_{j=1}^{k-1} (\zeta_{\kappa(j)} + T_{\text{fly}, i}) + \zeta_{\kappa(k)}(n), \sum_{j=1}^{k-1} (\zeta_{\kappa(j)} + T_{\text{fly}, i}) \right) \]

for even sub-phases with \( k \in \{1, \ldots, \Omega^k(n) + K - 1\} \). Therefore, within each odd sub-period \( 2k-1 \), the UAV should hover at the \( \kappa(k) \)-th hovering location \( (x_{\kappa(k)}, y_{\kappa(k)}, H) \), i.e.,

\[ \mathbf{q}(t) = q^k_{\text{opt}}(t), \]

\[ 2 \text{ in order for the UAV to visit all the } \Omega^k(n) + K \text{ hovering locations, we consider } T \geq T_{\text{fly}} \text{ in this paper, and leave the case with } T < T_{\text{fly}} \text{ for future work.} \]
B. Resource Allocation Optimization with Given UAV Trajectory

Under the obtained successive hover-and-fly trajectory, we maximize the uplink common throughput of all users by optimizing the transmission mode \( \{\rho_k(t)\} \) and the power allocation \( \{P(t)\} \) and \( \{Q_k(t)\} \), jointly with the hovering durations \( \{\tau_\omega\} \) and \( \{\varsigma_k\} \), which are optimization variables that will be determined next. The transmission policy in this sub-phase is based on the obtained hover-and-fly trajectory design is asymptotically optimal for the uplink common throughput maximization problem is reformulated as the following problem (P3), in which the optimization variables include \( \{\varsigma_k\} \), \( \{Q_k^{\text{hover}}\} \), \( \{\tau_\omega\} \), \( \{\tau_k^{\text{fly}}\} \), \( \{Q_k^{\text{fly}}\} \), and \( R \). 

\[
\begin{align*}
(\text{P3: max } R) & \quad \text{s.t. } \bar{R}_k(\varsigma_k, Q_k^{\text{hover}}) + R_k^{\text{fly}}(\{\tau_k^{\text{fly}}\}, Q_k^{\text{fly}}) \geq R, \forall k \in K \\
& \quad \varsigma_k Q_k^{\text{hover}} + \sum_{n=1}^{N} \tau_k^{\text{fly}}[n] Q_k^{\text{fly}}[n] \leq \bar{E}_k^{\text{hover}}(\{\tau_\omega, P\}) + \bar{E}_k^{\text{fly}}(\{\tau_k^{\text{fly}}[n], P_{\text{peak}}\}), \forall k \in K \\
& \quad \varsigma_k \geq 0, \forall k \in K, \tau_\omega \geq 0, \forall \omega \in \{1, \ldots, \Omega^{(\mu_{\text{mw}})}\} \\
& \quad \sum_{k=1}^{K} \varsigma_k + \sum_{\omega=1}^{\Omega^{(\mu_{\text{mw}})}} \tau_\omega = T - T^{\text{fly}} \\
& \quad \tau_k^{\text{fly}}[n] \geq 0, \forall n \in N, k \in K \cup \{0\} \\
& \quad \sum_{k=0}^{K} \tau_k^{\text{fly}}[n] = \delta, \forall n \in N. 
\end{align*}
\]

Note that although problem (P3) is non-convex due to the coupling between some variables (e.g., between \( \varsigma_k \) and \( Q_k^{\text{hover}} \)). Fortunately, via change of variables (e.g., introducing \( \bar{E}_k^{\text{hover}} = \varsigma_k Q_k^{\text{hover}} \)), we can transform problem (P3) into a convex optimization problem, which can thus be solved via standard convex optimization techniques. By combining the optimal solution to (P3) with the successive hover-and-fly trajectory in (25) and (26), an efficient solution to (P1) is obtained.

Remark 4.1: It is worth noting that the proposed successive hover-and-fly trajectory design is asymptotically optimal for (P1) when \( T \to \infty \), as the flying time becomes negligible as compared to the hovering time. In this case, the obtained uplink common throughput approaches the optimal value of (P2), which serves as the upper bound for that of (P1).

V. Numerical Results

In this section, we present numerical results to validate the performance of our proposed trajectory design as compared to the following benchmark scheme, with a static hovering UAV. In this benchmark scheme, the UAV hovers at a fixed location \((x^{\text{static}}, y^{\text{static}}, H)\) that is searched to maximize the uplink common throughput of all ground users. \((x^{\text{static}}, y^{\text{static}})\) can be obtained by solving problem (P2) under each given fixed location, and then finding the optimal location via a 2D exhaustive search.

In the simulation, we consider a system with \( K = 9 \) ground users that are randomly distributed within a 2D area of \( 20 \times 20 \) m², as shown in Fig. 2. The UAV flies at a fixed altitude \( H = 5 \) m. The receiver noise power is assumed to be \( \sigma^2 = -70 \) dBm. The channel power gain at the reference distance \( d_0 = 1 \) m is set as \( \beta_0 = -30 \) dB. The energy harvesting efficiency is set as \( \eta = 50\% \). The maximum speed of the UAV is \( V_{\text{max}} = 10 \) m/s.

For illustration, Fig. 2 shows the optimal hovering locations for problem (P2), and the successive hovering-and-fly trajectory
under the 9-user setup, where $T = 40$ s and $P_{\text{peak}} = 100$ W. It is observed that there are $\Omega_{\text{opt}} = 4$ optimal hovering locations for WPT and a total of $\Omega_{\text{opt}} + K = 13$ optimal hovering locations for problem (P2).

Fig. 3 shows the uplink common throughput of the $K$ users versus the flight duration $T$, in which $P_{\text{peak}} = 100$ W. It is observed that the proposed successive hover-and-fly trajectory (jointly with the optimal transmission resource allocation) achieves higher common throughput than the static-hovering benchmark, and the performance gain becomes more substantial when $T$ becomes larger. Furthermore, with sufficiently large $T$, the successive hover-and-fly trajectory is observed to have a similar performance as the upper bound by the multi-location-hovering solution to (P2) with the maximum UAV speed constraint ignored. This is consistent with Remark 4.1.

VI. CONCLUSION

In this paper, we investigated the common throughput maximization problem in a new UAV-enabled WPCN, subject to the UAV’s maximum speed constraint and the users’ energy neutrality constraints. We jointly optimized the UAV trajectory and the transmission resource allocation in both downlink WPT and uplink WIT. To solve this challenging problem, we first considered the ideal case without the maximum UAV speed constraint and solved the relaxed problem optimally. The optimal solution showed that the UAV should successively hover above two sets of optimal ground locations for downlink WPT and uplink WIT, respectively. Next, based on the optimal solution to the relaxed problem, we proposed a successive hover-and-fly trajectory to solve the problem with the maximum UAV speed constraint considered. Numerical results showed that the proposed design achieves near-optimal performance when the flight period is sufficiently large.

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