Energy Minimization in RIS-Assisted UAV-Enabled Wireless Power Transfer Systems

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Abstract—Unmanned aerial vehicle (UAV)-enabled wireless power transfer (WPT) systems offer significant advantages in coverage and deployment flexibility, but suffer from endurance limitations due to the limited onboard energy. This article proposes to improve the energy efficiency of UAV-enabled WPT systems with multiple ground sensors by utilizing reconfigurable intelligent surface (RIS). Specifically, the total energy consumption of the UAV is minimized, while meeting the energy requirement of each sensor. First, we consider a fly-hover-broadcast (FHB) protocol, in which the UAV radiates radio-frequency (RF) signals only at several hovering locations. The energy minimization problem is formulated to jointly optimize the UAV’s trajectory, hovering time, and the RIS’s reflection coefficients. To solve this complex nonconvex problem, we propose an efficient algorithm. Specifically, the successive convex approximation (SCA) framework is adopted to jointly optimize the UAV’s trajectory and hovering time, in which a minorization-maximization (MM) algorithm that maximizes the minimum charged energy of all sensors is provided to update the reflection coefficients. Then, we investigate the general scenario in which the RF signals are radiated during the flight, aiming to minimize the total energy consumption of the UAV by jointly optimizing the UAV’s trajectory, flight time, and the RIS’s reflection coefficients. By applying the path discretization (PD) protocol, the optimization problem is formulated with a finite number of variables. A high-quality solution for this more challenging problem is obtained. Finally, our simulation results demonstrate the effectiveness of the proposed algorithm and the benefits of RIS in energy saving.

Index Terms—Minorization–maximization (MM), reconfigurable intelligent surface (RIS), unmanned aerial vehicle (UAV), wireless power transfer (WPT).

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I. INTRODUCTION

WIRELESS power transfer (WPT)-enabled by radio-frequency (RF) transmission can continuously and steadily replenish energy for low-power devices in future Internet of Things (IoT) networks [1], [2]. Without a wired connection for power supply, IoT devices can be deployed more flexibly and cost less to install, charge, and maintain [3]. Nevertheless, traditional WPT systems with fixed energy transmitters are limited in coverage and energy efficiency due to the severe signal attenuation. Dense deployment of energy transmitters may lead to high construction and energy costs.

Unmanned aerial vehicles (UAVs) operating at low altitudes are with high maneuverability and flexibility, and can be dispatched as aerial platforms for data collectors, access points, relays, etc., [4], [5]. As a promising solution to improve the quality of wireless communications, the application of UAVs has received extensive attention in recent years. By flying close to the energy devices, UAVs are able to improve the energy harvesting efficiency of WPT systems and wireless-powered communication networks (WPCNs) [6]–[8]. In addition, in harsh environments, such as forests, mountains, deserts, and disaster areas, UAV-enabled WPT can be a more practical and cost-effective solution to extend the lifetime of low-power sensors and IoT devices than terrestrial infrastructures. However, when deploying UAVs in urban areas to track the cars or monitor the dynamic traffic status, the communication link between the UAVs and the ground devices may suffer from the blockages due to the high dense trees, buildings, advertising board, etc. This will result in lower energy harvesting efficiency.

As a promising technology for the future wireless communication networks, reconfigurable intelligent surface (RIS) has attracted extensive research attention recently. It improves the quality of wireless communications by reconfiguring the radio propagation environment [9], [10]. With the aid of RISs, the performance of the existing wireless communication systems can be improved significantly [11]–[13]. Furthermore, the integration of RIS into various communication systems has been proposed, for multicell MIMO communications [14], full-duplex cellular communications [15], mobile-edge computing [16], and simultaneous wireless information and power transfer (SWIPT) [17]. An RIS is a low-power device with no RF chain, which is a programmable metamaterial planar surface that consists of a large number of passive reflecting elements [18]. Each element independently reflects the incident signal while inducing a digitally controlled phase shift [19]. Thanks to the developments in metamaterials, the phase shifts

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can be reconfigured in real time [20]. When they are properly adjusted, an RIS can provide substantial passive beamforming gains. Moreover, the signal power can at a given receiver can be enhanced by constructively superimposing the reflected and direct signals. It is a cost-efficient solution to integrate the RIS into UAV-enabled communication systems [21]–[23], and has demonstrated considerable performance enhancement in a variety of scenarios, such as data collection [24], mobile relaying [25], and symbiotic radio systems [26].

Inspired by these advantages, the integration of RIS in UAV communications with WPT has been explored in various scenarios. Zhang et al. [27] proposed a device called the power and data beacon (PDB) to enable the downlink energy and information delivery in systems with a vast number of IoT nodes, and considered the deployment of RIS to assist the information transmission from UAV to PDBs. Based on the technologies of RIS and UAV-mounted cell-free massive MIMO, Khalil et al. [28] proposed a novel framework for time-division energy harvesting of IoT devices. Considering a UAV-enabled WPCN in which IoT devices upload data using the harvested energy with the assistance of RIS, Khac Nguyen et al. [29] utilized deep reinforcement learning to maximize the total network rate. In [30], the sum-rate maximization problem was investigated for an RIS-empowered UAV SWIPT scheme, in which a single-antenna UAV simultaneously transmits signals to multiple users, each of which harvests energy with a power splitter. However, as an important challenge hindering the practical application of UAV, the energy consumption has not been considered in the above RIS-empowered WPT scenarios.

In this article, we consider an RIS-assisted UAV-enabled WPT system, where the UAV is dispatched to provide the required power for multiple ground sensors with minimal energy consumption assisted by an RIS. To maximize the harvested energy, unlike time-division energy transfer scenarios [27], [28], all sensors should always receive the RF signals in our considered scenarios. In this case, it is not optimal to align the phase of the signal transmitted through one UAV-RIS-sensor link with that through the corresponding UAV-sensor direct link. Although the popular semidefinite relaxation (SDR)-based method can be adopted to solve the problems, it has high computational complexity. To address this issue, efficient algorithms are developed for solving the formulated problems. Specifically, we summarize the main contributions of our work as follows.

1) To the best of our knowledge, this is the first attempt to explore the benefits of reducing the system energy consumption by deploying an RIS in a UAV-enabled WPT system. Specifically, we consider a WPT system with multiple sensors, and propose to minimize the total energy consumption of the UAV while ensuring sufficient power supply for all sensors. Due to the continuous reception of RF signals by all sensors, the variables in the energy constraints of the energy minimization problems are coupled. Moreover, the complicated nonconvex expression of energy consumption and the unit-modulus constraints aggravate the difficulty of solving these problems.

2) Under the fly-hover-broadcast (FHB) protocol, we formulate the energy minimization problem for a special scenario and propose an efficient iterative algorithm to solve it. The FHB protocol requires the UAV to visit several hovering locations in sequence and to radiate RF signals only at those locations, which can also serve as the performance lower bound of RIS-assisted UAV-enabled WPT systems. We design an efficient iterative algorithm based on the successive convex approximation (SCA) framework and the minorization–maximization (MM) method. Specifically, in the inner iteration, an MM algorithm is used to optimize the reflection coefficients of the RIS by maximizing the minimum charged energy of all sensors.

3) We extend the proposed method to solve the energy minimization problem in the general scenario. Specifically, we apply a path discretization (PD) protocol [31] that enables the UAV to radiate RF signals during its flight, and formulate the problem with a finite number of variables. Note that the propulsion energy of UAV accounts for the vast majority of the total energy consumption. The PD protocol brings significant energy saving by reducing the total flight time and providing more freedom for the planning of trajectory and flying speed.

4) Simulation results validate the energy efficiency improvement brought by an RIS over traditional UAV-enabled WPT systems, and verify the performance superiority of the PD protocol over the FHB protocol. Simulation results also validate the performance advantages of the proposed algorithms over the SDR-based benchmark.

The remainder of this article is organized as follows. Section II describes the system model. In Section III, we formulate the energy minimization problem under the FHB protocol, and develop an efficient algorithm. In Section IV, the proposed method is extended to the general scenario under the PD protocol. Extensive simulation results are shown in Section V. Finally, conclusions are drawn in Section VI.

**Notations:** Boldface lowercase and uppercase letters, respectively, denote vectors and matrices. $j$ and $\mathbb{C}$ denote the imaginary unit $\sqrt{-1}$ and the complex field, respectively. The conjugate, transpose, Hermitian, and trace of a matrix $X$ are denoted by $X^*$, $X^T$, $X^H$, and $\text{Tr}(X)$, respectively. For a vector $x$, $\|x\|_1$ and $\|x\|_2$ are its $l_1$- and $l_2$-norm, respectively. $|x|$, $\text{Re}(x)$, $\mathbb{E}[x]$, and $\angle(x)$ denote the absolute value, real part, expectation, and angle of a scalar $x$, respectively.

## II. System Model

Consider a WPT system as shown in Fig. 1, where one rotary-wing UAV with a single transmit antenna is dispatched as a mobile power transmitter to serve $K$ ground sensors with the aid of an RIS. The UAV is assumed to fly at a fixed altitude $H_U$ with the maximum speed of $V_{\text{max}}$ and a fixed radiated power $P_r$. Each sensor is equipped with a single receive antenna and a rechargeable battery. The required energy for sensor $k$ is denoted by $E_{k}^{\text{req}}$. The positions of all
sensors are *apriori* known by the UAV. During each UAV’s flight, all sensors continuously charge themselves by harvesting energy from the radiated RF signals, which is enhanced by the RIS. To facilitate the expression in the following discussion, we express the $x$ and $y$ coordinates of the devices by the real and imaginary parts of a complex number, respectively. For instance, the coordinates of sensor $k$ is denoted by $q_{k,x} = q_{k}^x + j q_{k}^y$. Additionally, the RIS is deployed at $q_{R} = q_{R}^x + j q_{R}^y$ with altitude $H_{R}$.

For a rotary-wing UAV with speed $v$, the propulsion power can be modeled as [31, eq. (12)]

$$
P_{p}(v) = P_{0} \left( 1 + \frac{3v^2}{U_{tip}^2} \right) + P_{t} \left( 1 + \sqrt{1 + \frac{v^4}{4v_{0}^4} - \frac{3v^2}{2v_{0}^2}} \right) + \frac{1}{2} d_{0} \rho s A v^{3}. \tag{1}$$

The physical meanings of the parameters in (1) are explained in Table I, and the definitions of which are detailed in [31, Appendix].

For simplicity, we assume that the RIS is equipped with a uniform linear array consisting of $M$ passive reflecting elements. Denote by $\theta_{m,q}$ the phase shift of the $m$th reflecting element of the RIS when the UAV is at location $q = q^x + j q^y$. The reflection coefficient vector is defined as $\phi_q = \left[ e^{j \theta_{1,q}}, \ldots, e^{j \theta_{M,q}} \right]^T$. The elements in $\phi_q$ satisfy

$$
\theta_{m,q} \in [0, 2\pi), \quad m = 1, \ldots, M. \tag{2}
$$

When the UAV is at location $q$, the baseband channels from the UAV to sensor $k$, from the UAV to the RIS, and from the RIS to sensor $k$ are denoted by $g_{d,k,q} \in \mathbb{C}^{1 \times 1}$, $g_{i,k,q} \in \mathbb{C}^{M \times 1}$, and $g_{r,k,q} \in \mathbb{C}^{M \times 1}$, respectively. The Rician fading is assumed for all channels. The channels related to the RIS are modeled as

$$
g_{i,q} = \sqrt{\beta_{i,q}} \left( \frac{\kappa_{i}}{\kappa_{i} + 1} g_{i}^{{\text{LoS}}} + \frac{1}{\kappa_{i} + 1} g_{i}^{{\text{NLoS}}} \right) \tag{3}
g_{r,k,q} = \sqrt{\beta_{r,k}} \left( \frac{\kappa_{r}}{\kappa_{r} + 1} g_{r,k}^{{\text{LoS}}} + \frac{1}{\kappa_{r} + 1} g_{r,k}^{{\text{NLoS}}} \right) \tag{4}
$$

where $\beta_{i,q}$ and $\beta_{r,k}$ represent the large-scale fading coefficients, $\kappa_{i}$ and $\kappa_{r}$ denote the Rician factors, $g_{i}^{{\text{LoS}}}$ and $g_{r,k}^{{\text{LoS}}}$ denote the deterministic LoS channels, and $g_{i}^{{\text{NLoS}}}$ and $g_{r,k}^{{\text{NLoS}}}$ are the small-scale channel fading. Each element of $g_{i,q}^{{\text{NLoS}}}$ and $g_{r,k,q}^{{\text{NLoS}}}$ independently follows the circularly symmetric complex Gaussian (CGCS) distribution with zero mean and unit variance. The expressions of $\beta_{i,q}$ and $\beta_{r,k}$ are, respectively, given by

$$
\beta_{i,q} = \frac{\beta_{0}}{\left( |q - q_{R}| + (H_{U} - H_{R}) \right)^{\alpha_{i}/2}} \quad \alpha_{r} \leq \beta_{0} \quad \tag{5}
\beta_{r,k} = \frac{\beta_{0}}{\left( |q_{S,k} - q_{R}| + H_{R}^{2} \right)^{\alpha_{r}/2}} \quad \alpha_{r} \leq \beta_{0} \quad \tag{6}
$$

where $\beta_{0}$ is the channel gain at the reference distance of 1 m, $d_{t,q}$ is the distance between the UAV and the RIS, $d_{r,k}$ is the distance between the RIS and sensor $k$, and the corresponding path-loss coefficients are denoted by $\alpha_{t}$ and $\alpha_{r}$, respectively. Based on the assumption of uniform linear array, the LoS components of the RIS-related channels $g_{i,q}^{{\text{LoS}}}$ and $g_{r,k,q}^{{\text{LoS}}}$ are, respectively, modeled as

$$
g_{i,q}^{{\text{LoS}}} = e^{-\frac{j 2\pi d_{t,q}}{\lambda}} \left[ 1, e^{-\frac{j 2\pi}{\lambda} \cos \phi_{1,q}}, \ldots, e^{-\frac{j 2\pi M - 1 \cdot \lambda}{\lambda} \cos \phi_{M,q}} \right]^T \tag{7}
g_{r,k,q}^{{\text{LoS}}} = e^{-\frac{j 2\pi d_{r,k}}{\lambda}} \left[ 1, e^{-\frac{j 2\pi}{\lambda} \cos \phi_{1,q}}, \ldots, e^{-\frac{j 2\pi M - 1 \cdot \lambda}{\lambda} \cos \phi_{M,q}} \right]^T \tag{8}
$$

where $\lambda$ and $d$ denote the wavelength and element spacing of the RIS, respectively, and $\cos \phi_{m,q} = [(q_{R}^{x} - q^{x})/d_{t,q}]$ and $\cos \phi_{m,k} = [(q_{S,k}^{x} - q^{x})/d_{r,k}]$ represent the cosine of Angle of Arrival (AoA) and Angle of Departure (AoD), respectively. Similarly, the direct link from the UAV to sensor $k$ is modeled as

$$
g_{d,k,q} = \sqrt{\beta_{d,k,q}} \left( \frac{\kappa_{d}}{\kappa_{d} + 1} g_{d,k,q}^{{\text{LoS}}} + \frac{1}{\kappa_{d} + 1} g_{d,k,q}^{{\text{NLoS}}} \right) \tag{9}
$$

where $\beta_{d,k,q} = (\beta_{0}/d_{d,k,q}^{2})$ is the large-scale fading coefficient, $d_{d,k,q} = \sqrt{|q - q_{S,k}|^{2} + H_{U}^{2}}$ is the distance between the UAV and sensor $k$, $g_{d,k,q}^{{\text{LoS}}} = \exp(-j(2\pi/\lambda)d_{d,k,q})$ is the LoS channel component, and the NLoS channel component $g_{d,k,q}^{{\text{NLoS}}}$ follows zero-mean and unit-variance CGCS distribution. Let us introduce a diagonal reflection coefficient matrix $\Phi_q = \text{diag}(\phi_q)$. Then, we can express the equivalent channel spanning from the UAV to sensor $k$ as $g_{k,q} = g_{d,k,q} + g_{d,k,q}^{H} \Phi_{q} g_{r,k,q}$. Accordingly, the received power at sensor $k$ from the RF signal radiated at location $q$ is given by

$$
P_{k,q} = P_{t} \left| g_{d,k,q} + g_{r,k,q}^{H} \Phi_{q} g_{r,k,q} \right|^{2}. \tag{10}$$
Without loss of generality, we assume the same energy conversion efficiency \( \eta \) for all sensors.

Note that in practice, although channel estimation methods for RIS-assisted networks have been proposed in the existing literature\,[32], it is impossible to estimate the small-scale channel fading before the flight. Hence, we design the system based on the long-term channel state information. To this end, the following theorem provides the expectation of the received power at each sensor \( \hat{P}_{k,q} = \mathbb{E}[P_{k,q}] \).

Theorem 1: The expected received power \( \hat{P}_{k,q} \) at sensor \( k \) is given by

\[
\hat{P}_{k,q} = P_l \left( \frac{k_l \kappa_l \beta_{l,k} \hat{P}_{l,q} (k_l + 1)(k_l + 1)}{(k_l + 1)(k_l + 1)(k_l + 1)} \psi_{k,q}^H \psi_{k,q} \right. \\
+ 2 \left. \frac{\kappa_l \kappa_l \beta_{l,k} \hat{P}_{l,q} (k_l + 1)(k_l + 1)}{(k_l + 1)(k_l + 1)(k_l + 1)} \text{Re} \left( \psi_{k,q}^H \phi_k \right) \right) + \beta_{d,k,q} + \frac{M(k_l + \kappa_l + 1) \beta_{l,k} \beta_{l,q} \hat{P}_{l,q}}{(k_l + 1)(k_l + 1)}
\]

(11)

where

\[
\psi_{k,m,q} = \frac{2 \pi}{\lambda} \left[(d_{k,m,q} + d_{k,l} - d_{k,q}) + d(\cos \omega_{k,l} - \cos \omega_{k,q})(m - 1)\right]
\]

(12)

\[
\psi_{k,q} = \left[e^{-j \phi_{k,1,q}}, \ldots, e^{-j \phi_{k,M,q}}\right]^T.
\]

(13)

Proof: Refer to Appendix A.

The results in the above theorem will be used in the following sections for the system design.

III. FLY-HOVER-BROADCAST PROTOCOL

The widely adopted FHB protocol is intuitive and easy to implement in practice, which also provides a performance lower bound for the general scenario. In this section, we aim to minimize the total energy consumption of the UAV based on the FHB protocol. An efficient algorithm is developed to solve the formulated problem.

A. Protocol and Energy Consumption Model

Under the FHB protocol, it is assumed that the UAV radiates RF signals only when hovering. The trajectory consists of the initial and final locations \( q_l \) and \( q_f \), and \( L - 1 \) hovering locations connected by \( L \) straight path segments. We denote the \( l \)-th hovering location by \( q_{l,U} = q_{l,U}^x + j q_{l,U}^y \) for \( l \in \mathcal{L}_b \), where \( \mathcal{L}_b = \{1, \ldots, L - 1\} \). On each flight, the UAV starts from \( q_l \), successively visits the hovering locations, and finally arrives at \( q_f \). Then, the total trajectory is denoted by \( q_U = [q_{U,0}, \ldots, q_{U,L}]^T \in \mathbb{C}^{(L+1) \times 1} \) with

\[
q_{U,0} = q_l, \quad q_{U,L} = q_f.
\]

It was derived in\,[31] that each rotary-wing UAV has a maximum-range (MR) speed \( v_{mr} \) that maximizes the total travel distance with any given onboard energy, which can be found from the plot of propulsion power \( P_p(v) \) versus UAV speed \( v \). With the MR speed \( v_{mr} \), the flight time of the UAV along the \( l \)-th path segment is given by \( \left( d_{l,U} - q_{l,U,g} - 1 \right)/v_{mr} \).

By substituting \( v = v_{mr} \) into (1), we have the MR energy consumption \( P_{mr}^p = P_p(v_{mr}) \). Similarly, the hovering energy consumption is derived as \( P_{hov}^p = P_v(0) = P_0 + P_l \). Denoting the hovering time of the UAV at the \( l \)-th hovering location by \( t_l \), we have the total energy consumption of the UAV as follows:

\[
P_{U}^{\text{FHB}}(q_{U}, t) = P_{mr}^p \sum_{l=1}^{L} |q_{U,l} - q_{U,l-1}| v_{mr} + \sum_{l \in \mathcal{L}_b} (P_{hov}^p + P_l) t_l
\]

(15)

where \( t = [t_1, \ldots, t_{L-1}]^T \).

B. Problem Formulation

When the UAV is at the \( l \)-th hovering location, we denote the phase shift of the \( m \)-th reflecting element of the RIS by \( \theta_{m,l} \), \( \psi_l = [e^{j \theta_{1,l}}, \ldots, e^{j \theta_{M,l}}]^T \) and \( \Phi_l = \text{diag}(\psi_l) \) are also defined for \( l \in \mathcal{L}_b \), which satisfies

\[
\theta_{m,l} \in [0, 2\pi], \quad m = 1, \ldots, M, \quad l \in \mathcal{L}_b.
\]

(16)

Let \( \beta_{l,k,l} \), \( \beta_{l,k,l} \), and \( \psi_{k,l} \) denote the values of \( \beta_{l,k,l} \), \( \beta_{l,k,l} \), and \( \psi_{k,l} \) when the UAV is at the \( l \)-th hovering location, respectively. From (11), the expectation of the received power at sensor \( k \) is given by

\[
\hat{P}_{k,l} = P_l \left( \frac{k_l \kappa_l \beta_{l,k,l} \hat{P}_{l,q} (k_l + 1)(k_l + 1)}{(k_l + 1)(k_l + 1)(k_l + 1)} \psi_{k,l}^H \psi_{k,l} \right. \\
+ 2 \left. \frac{k_l \kappa_l \beta_{l,k,l} \hat{P}_{l,q} (k_l + 1)(k_l + 1)}{(k_l + 1)(k_l + 1)(k_l + 1)} \text{Re} \left( \psi_{k,l}^H \phi_k \right) \right) + \beta_{d,k,l} + \frac{M(k_l + \kappa_l + 1) \beta_{l,k} \beta_{l,q} \hat{P}_{l,q}}{(k_l + 1)(k_l + 1)}.
\]

(17)

In this section, we minimize the UAV energy consumption while providing the required energy for all sensors under the FHB protocol, via jointly optimizing the trajectory \( q_{U} \), the hovering time \( t \), and the reflection coefficient vectors \( \{\psi_l\} \).

The energy minimization problem can be formulated as follows:

\[
\min_{q_U, t, \{\psi_l\}} E_{U}^{\text{FHB}}(q_{U}, t) \quad \text{s.t.} \quad t_l \geq 0, \quad l \in \mathcal{L}_b
\]

(18a)

\[
\eta \sum_{l \in \mathcal{L}_b} t_l \hat{P}_{k,l} \geq \varepsilon_{k,l}, \quad k = 1, \ldots, K
\]

(14), (16).

(18c)

The main notations used in problem (18) are summarized in Table II. In problem (18), the trajectory \( q_{U} \), the hovering time \( t \), and the reflection coefficient vectors \( \{\psi_l\} \) are jointly optimized. By applying the MR speed \( v_{mr} \), the objective function is transformed to a convex function. However, constraints (16) and (18c) are still nonconvex, and all variables are coupled in (18c). In the following, we propose an efficient method for this complicated problem by decoupling it into two subproblems.

C. Optimizing the Trajectory \( q_{U} \) and Hovering Time \( t \)

In this section, we propose an iterative algorithm based on the SCA method to jointly optimize \( q_{U} \) and \( t \) given \( \{\psi_l\} \). From
From (17), it can be found that problem (18), the subproblem of (19), can be introduced with limited approximation $\psi$ by $\bar{U}_{n}$. The following inequalities:

$$\expansion \{ \delta \} \geq \sum \eta \psi \{ \delta \} \beta_{d, k}$$

we utilize the SCA method to transform it to several convex expansion is a lower bound of a convex function, we have the following approximation error:

$$\beta_{d, k} \geq \frac{\beta_{0}}{\left( \left| q_{U, l} - q_{R} \right|^{2} + (H_{U} - H_{R})^{2} \right)^{\frac{\eta}{2}}} - \alpha_{d} \beta_{0} \left( \left| q_{U, l} - q_{R} \right|^{2} - \left| q_{U, l} - q_{R} \right|^{2} \right) - 2 \left( \left| q_{U, l} - q_{R} \right|^{2} + (H_{U} - H_{R})^{2} \right)^{\frac{\eta}{2} + 1} \leq \beta_{d, k}$$

where $q_{U, l}$ is the value of $q_{U, l}$ at the $n$th iteration. Then, the problem to be solved at the $n$th SCA iteration can be formulated as follows:

$$\min_{q_{U}, \{ y_{a, k, l} \}} \mathbb{E}_{U}^{FHB} \left( q_{U}, t \right)$$

s.t. $\eta_{FHB} \left( \bar{U}_{1}, \{ y_{a, k, l} \} \right)$

$$\bar{U}_{k, l} \leq \bar{U}_{1, k, l} + U_{3, k, l} \psi_{k, l} + U_{2, k, l} \delta_{d, k} \leq \bar{U}_{1, k, l} + U_{3, k, l} \psi_{k, l} + U_{2, k, l} \delta_{d, k}$$

Then, constraint (18c) is approximated as

$$\eta_{FHB} \sum_{l \in \mathcal{L}_{b}} P_{tl} \left( \frac{U_{1, k, l} + U_{3, k, l} \psi_{k, l} + U_{2, k, l} \delta_{d, k} \beta_{d, k} l} {k} \right) \geq 1, k = 1, \ldots, K.$$  

However, constraint (24) is still nonconvex. In the following, we utilize the SCA method to transform it to several convex constraints. First, by using the fact that the first-order Taylor expansion is a lower bound of a convex function, we have the following inequalities:

$$\beta_{d, k} \geq \frac{\beta_{0}}{\left( \left| q_{U, l} - q_{R} \right|^{2} + (H_{U} - H_{R})^{2} \right)^{\frac{\eta}{2}}} - \alpha_{d} \beta_{0} \left( \left| q_{U, l} - q_{R} \right|^{2} - \left| q_{U, l} - q_{R} \right|^{2} \right) - 2 \left( \left| q_{U, l} - q_{R} \right|^{2} + (H_{U} - H_{R})^{2} \right)^{\frac{\eta}{2} + 1} \leq \beta_{d, k}$$

Note that (27b) is still nonconvex, we introduce two sets of slack variables $\{ y_{a, k, l} \}$ and $\{ e_{k, l} \}$ to transform it as the following constraints:

$$\left( \bar{U}_{1, k, l} + U_{3, k, l} \right) y_{a, k, l} + U_{2, k, l} e_{k, l} \geq \frac{E_{k}^{eq} \varepsilon_{k, l}} {\eta P_{tl}}$$

$$\sum_{l \in \mathcal{L}_{b}} y_{a, k, l} \geq 0, k = 1, \ldots, K$$

$y_{a, k, l} \geq \frac{y_{a, k, l}} {y_{a, k, l}}$, $l \in \mathcal{L}_{b}, k = 1, \ldots, K$

and utilize the first-order Taylor expansion to transform (30) as

$$\sum_{l \in \mathcal{L}_{b}} \left( 2 \varepsilon_{k, l} e_{k, l} - e_{k, l}^{2} \right) \geq 1, k = 1, \ldots, K$$

where $e_{k, l}$ is the value of $e_{k, l}$ at the $n$th iteration. Finally, problem (27) is reformulated as

$$\min_{q_{U}, \{ y_{a, k, l} \}, \{ e_{k, l} \}} \mathbb{E}_{U}^{FHB} \left( q_{U}, t \right)$$

s.t. $\eta_{FHB} \left( \bar{U}_{1}, \{ y_{a, k, l} \} \right)$
Problem (32) is a convex problem that can be efficiently solved by the existing optimization tools, such as CVX. 

D. Optimizing the Reflection Coefficient Vectors \{\phi_i\}

In this section, we optimize \{\phi_i\} given \(q_t\) and \(t\). Note that the objective function of (18) is independent of \{\phi_i\}. Hence, the subproblem of \{\phi_i\} is a feasibility check problem. To improve convergence performance, a common approach is to strengthen the optimization objective to maximize the total oversupplied energy of all sensors [12], [13]. However, due to the energy requirement constraint (18c), the transformed subproblem is not guaranteed to be feasible, which may lead to early convergence of the algorithm. To address this, we set a more challenging optimization objective to maximize the minimum charged energy of all sensors instead. The corresponding subproblem is formulated as follows:

\[
\begin{align*}
\text{max} & \quad \epsilon \\
\text{s.t.} & \quad \eta \frac{E_{\text{eq}}}{E_{\text{k}}^k} \sum_{l \in L_b} t_{l} \hat{P}_{k,l} \geq \epsilon, \ k = 1, \ldots, K
\end{align*}
\]  
(33a)

\[
\begin{align*}
\text{s.t.} & \quad \eta \frac{E_{\text{eq}}}{E_{\text{k}}^k} \sum_{l \in L_b} t_{l} \hat{P}_{k,l} \geq \epsilon, \ k = 1, \ldots, K
\end{align*}
\]  
(33b)

where \(\epsilon\) is an auxiliary variable. To guarantee the feasibility, constraint (18c) in problem (33) is relaxed by removing the constraint \(\epsilon \geq 1\). In this article, we propose to obtain the solution of problem (18) by solving problems (32) and (33) alternately. Since the former involves the energy requirement constraint (28), the relaxation technique will not change the feasibility of the converged solution in problem (18). Note that constraint (16) imposes \(M(L-1)\) unit-modulus constraints on \{\phi_i\}. For schemes with large \(L\), Gaussian randomization in the SDR-based method incurs significant performance loss when solving problem (33).\(^1\)

1 Under general protocols, such as the PD protocol applied in Section IV, the value of \(L\) is much larger and the performance loss is more severe.

In the following, we propose a low-complexity algorithm to solve problem (33) based on the widely used MM method [15], [33]–[35].

To begin with, we reformulate problem (33) as a more tractable form. By defining

\[
\begin{align*}
A_{k,l} &\triangleq P_l \frac{k_{k,l} k_{\hat{b}_{k,l}} k_{\hat{b}_{k,l}}}{(k_{k,l} + 1)(k_{\hat{b}_{k,l}} + 1)} \psi_{k,l} \psi_{k,l}^H \\
\phi_{k,l} &\triangleq P_l \frac{\kappa_{k,l} k_{\hat{b}_{k,l}} k_{\hat{b}_{k,l}}}{(k_{k,l} + 1)(k_{\hat{b}_{k,l}} + 1)} \psi_{k,l} \\
\text{cons}\theta_{k,l} &\triangleq P_l \frac{\beta_{k,l}}{(k_{k,l} + 1)(k_{\hat{b}_{k,l}} + 1)} \\
\end{align*}
\]  
(34)

(35)

(36)

we can transform (11) as follows:

\[
\hat{P}_{k,l} = \phi_{k,l} A_{k,l} + 2 \text{Re} \{\phi_{k,l}^H \} + \text{cons}\theta_{k,l}.
\]  
(37)

Then, we define \(h_k(\phi) \triangleq (\eta / E_{\text{eq}}^k) \sum_{l \in L_b} t_{l} \hat{P}_{k,l}\) and transform it into the following quadratic form:

\[
\begin{align*}
h_k(\phi) &= \sum_{l \in L_b} \frac{\eta t_{l} E_{\text{eq}}^k}{E_{\text{k}}^k} \phi_{l} A_{l}^H \phi_{l} + 2 \sum_{l \in L_b} \frac{\eta t_{l} E_{\text{eq}}^k}{E_{\text{k}}^k} \text{Re} \{\phi_{l} A_{l}^H \phi_{l}\} \\
&\quad + \sum_{l \in L_b} \frac{\eta t_{l} E_{\text{eq}}^k}{E_{\text{k}}^k} \text{cons}\theta_{l} \\
&= \phi^H B_k \phi + 2 \text{Re} \{b_k^H \phi\} + \text{cons}\phi_k \\
\end{align*}
\]  
(38)

Finally, problem (33) is reformulated as follows:

\[
\begin{align*}
\text{max} & \quad \min_{\phi} h_k(\phi) \\
\text{s.t.} & \quad (16).
\end{align*}
\]  
(43a)

Note that the objective function of problem (43) is nondifferentiable. To address this, we replace it with the following smooth and convex lower bound [36]:

\[
\begin{align*}
\min_{\phi} h_k(\phi) &\approx f(\phi) \\
&= -\frac{1}{\mu} \log \left( \sum_{k=1}^{K} \exp(-\mu h_k(\phi)) \right) \\
\end{align*}
\]  
(44)

where \(\mu > 0\) is a smoothing parameter. In particular, the following inequalities hold:

\[
\begin{align*}
f(\phi) &\leq \min_{\phi} h_k(\phi) \\
&\leq f(\phi) + \frac{1}{\mu} \log(K).
\end{align*}
\]  
(45)

By replacing the objective function of problem (43) with \(f(\phi)\), a convex problem can be obtained. To utilize the MM method, the following theorem provides a tractable minorizing function of \(f(\phi)\) to formulate the surrogate problem at each iteration.

Theorem 2: Denote by \(\phi^r\) the solution at the \(r\)th iteration. For any feasible \(\phi, f(\phi)\) is minorized with \(\tilde{f}(\phi) \mid \phi^r\) as follows:

\[
\tilde{f}(\phi \mid \phi^r) = 2 \text{Re} \{u^H \phi\} + \text{cons}\phi_{\text{MM}}
\]  
(46)

where

\[
\begin{align*}
g_k(\phi^r) &\triangleq \frac{\exp(-\mu h_k(\phi^r))}{\sum_{k=1}^{K} \exp(-\mu h_k(\phi^r))} \\
c &\triangleq \sum_{k=1}^{K} g_k(\phi^r) (B_k^H \phi^r + b_k) \\
\alpha &\triangleq -2\mu \max_k \left\{ M \max_{l} \left\{ \lambda_{\max} \left( \frac{E_{\text{eq}}^k}{E_{\text{k}}^k} A_{k,l}^H A_{k,l}^H \right) \right\} + b_k^H b_k + 2\|B_k b_k\|_1 \right\} \\
u &\triangleq c - \alpha \phi^r \\
\text{cons}\phi_{\text{MM}} &\triangleq f(\phi^r) - 2 \text{Re} \{c^H \phi^r\} + 2\alpha M.
\end{align*}
\]  
(47)

\(\alpha\)\(^1\)

\[u \triangleq c - \alpha \phi^r + \text{cons}\phi_{\text{MM}}\]

\[\text{cons}\phi_{\text{MM}} \triangleq f(\phi^r) - 2 \text{Re} \{c^H \phi^r\} + 2\alpha M.
\]  
(49)

Proof: Refer to Appendix B.

\[\begin{align*}
\text{Proof:}\ &\text{Refer to Appendix B.}
\end{align*}
\]  
(50)

(51)
Algorithm 1 MM Algorithm for Solving Problem (33)

Initialize: Initial the number of iterations as \( r = 1 \). Set feasible \( \phi^* \), smoothing parameter \( \mu \), maximum number of iterations \( n_{\text{max}} \) and error tolerance \( \epsilon_e \).

1: repeat
2: Calculate \( \hat{\phi}_1 = \Re(\phi^*) \) and \( \hat{\phi}_2 = \Re(\phi_1) \);
3: Calculate \( v_1 = \hat{\phi}_1 - \phi^* \) and \( v_2 = \hat{\phi}_2 - \phi_1 - v_1 \);
4: Calculate step factor \( \sigma = \frac{\| v_1 \|}{\| v_2 \|} \);
5: Calculate \( \phi^{r+1} = \exp(j\angle u) \exp(-2\sigma v_1 + \sigma^2 v_2) \);
6: If \( f(\phi^{r+1}) < f(\phi^*) \), set \( \sigma = \frac{(\alpha - 1)}{2} \) and go to step 2;
7: Set \( r \leftarrow r + 1 \);
8: until \( \| f(\phi^{r+1}) - f(\phi^*) \| < \epsilon_e f(\phi^*) \) or \( r \geq n_{\text{max}} \);
9: If \( \min(h_k(\phi^{r+1})) < \min(h_k(\phi^*)) \), set \( \phi^{r+1} \leftarrow \phi^* \).

By replacing the objective function of problem (43) with (46), we obtain the iterative problem at the \( r \)th MM iteration

\[
\max \phi \quad 2\Re[u^H \phi] + \text{cons}_{\phi_{\text{MM}}} \quad \text{s.t. (16)}.
\]

It can be readily verified that the optimal solution of problem (52) is given by

\[
\phi^{r+1} = \exp(j\angle u) \quad (53)
\]

where \( \exp(\cdot) \) and \( \angle(\cdot) \) are elementwise operations.

Based on the above discussions, a modified MM algorithm is proposed to solve problem (33), the details of which are provided in Algorithm 1, where SQUAREM [37] theory is introduced to accelerate the convergence. Specifically, \( \phi^{r+1} = \Re(\phi^*) \) in step 2 represents the nonlinear fixed-point iteration map given in (53). Thanks to the guaranteed feasibility of problem (33), \( \phi \) can be efficiently optimized by Algorithm 1 with arbitrary \( q_U \) and \( t \). Furthermore, the works in [14], [33], and [35] have proved and verified the Karush–Kuhn–Tucker (KKT) optimality of the converged solution of MM algorithm, which indicates that Algorithm 1 can obtain a KKT optimal solution of the relaxed problem (43) with objective function \( f(\phi) \). Moreover, when \( \mu \) is sufficiently large, the approximation in (44) is tight, and the converged solution is approximately KKT optimal for problem (33).

E. Algorithm Development

Based on the above discussions, we propose an effective and efficient algorithm for solving problem (18) in Algorithm 2, named SCA-MM. In step 5 of Algorithm 2, Algorithm 1 is utilized to calculate the optimal \( \phi^{n+1}_r \), where \( \phi^n \) in Algorithm 2 is chosen as the initial feasible \( \phi^* \) of Algorithm 1. In the later stage of Algorithm 2, a large \( \mu \) is required to improve the approximation accuracy of \( f(\phi) \) in (45). On the contrary, a large \( \mu \) may result in premature convergence to a local stationary point. To take into account both the solution’s optimality and the convergence speed, an adjustment factor \( \iota \) is introduced in step 6, which gradually increases \( \mu \) during iterations. Recall that the approximation (20) is introduced in constraint (28). Hence, the optimal solution to problem (32) is not guaranteed to satisfy constraint (18c). Although this issue will be addressed when problem (32) is solved again in a subsequent iteration, Algorithm 2 may not generate monotonically decreasing objective function value of problem (18). However, the simulations of convergence in Section V show that the fluctuations are not significant.

In the following, we analyze the computational complexity of Algorithm 2, which mainly lies in solving problem (32) in step 4 and calculating \( \phi^{n+1} \) in step 5. First, since problem (32) involves only linear matrix inequality (LMI) and second-order cone (SoC) constraints, it can be solved by a standard interior point method [38], whose computational complexity is given by

\[
O\left(\sum_{j=1}^{J} b_j + 2\underbrace{\sum_{i=1}^{I} a_i^2 + n^3}_{\text{SoC}}\right)
\]

where \( n \) represents the number of variables, and \( J \) and \( I \) denote the number of LMI and SoC constraints with sizes \( \{b_j\} \) and \( \{a_i\} \), respectively. Based on the above general expression, the complexity order of solving problem (32) can be derived as

\[
O_{\text{Alg.2}} = O(\sqrt{(5K + 3)(L - 1)} + 2K(n^2K(L - 1)^2 + nK(L - 1)^3 + n^3)),
\]

which is of order \( O_{\text{Alg.2}} = O(n_{\text{MM}}(K - 1)^2M^2 + \underbrace{M^2}_{\text{LMI}}) \) and \( O(\underbrace{K(L - 1)^2M^2 + (L - 1)M}_{\text{SoC}}) \), respectively. Denote the number of iterations required for Algorithm 1 to converge by \( n_{\text{MM}} \). Then, the complexity of calculating \( \phi^{n+1} \) is of order

\[
O_{\text{Alg.2}} = O(n_{\text{MM}}(K - 1)^2M^2 + \underbrace{M^2}_{\text{LMI}}).
\]

Finally, the overall complexity of Algorithm 2 is given by

\[
O_{\text{Alg.2}} = O_{\text{Alg.2}} + O_{\text{Alg.2}}.
\]

IV. PATH DISCRETIZATION PROTOCOL

In order to maximize the harvested energy, the RF signals should be radiated during the UAV's flight, which is not considered in the FHB protocol for simplicity. In this section, the general scenario is studied under the PD protocol. Specifically,
we solve the corresponding problem by extending the proposed method in the previous section.

A. Protocol and Energy Consumption Model

A common method to deal with the continuous flying trajectory of UAV is time discretization, where the predetermined duration of entire flight is divided into several time slots. However, this approach is not applicable to our work due to the UAV energy consumption, which is related to the flight time. To address this issue, we adopt the PD method. Specifically, the UAV trajectory is discretized into \( L \) path segments that are unequal in length. When the \( l \)th path segment is sufficiently short, it can be approximated as the line between its starting point \( q_{U,l-1} \) and ending point \( q_{U,l} \), where \( q_{U,l} = q_{U,l-1} + \rho_{U,l} \). Then, the total trajectory is denoted by \( q_U = [q_{U,0}, \ldots, q_{U,L}]^T \in \mathbb{C}^{(L+1) \times 1} \), where the constraints in (14) still hold.

The following constraints are introduced on the length of path segments \( \{\delta_l\} \):

\[
\delta_l = |q_{U,l} - q_{U,l-1}| \leq \Delta_{\text{max}}, \quad l \in \mathcal{L}_a
\]  
(54)

where \( \Delta_{\text{max}} \) is the maximum length of each path segment and \( \mathcal{L}_a = \{1, \ldots, L \} \). It is assumed that the UAV flies at a constant speed at each path segment. Due to the high mobility of rotary-wing UAV, the acceleration and deceleration process is ignored. In addition, the value of \( \Delta_{\text{max}} \) should be chosen appropriately so that the distance from the UAV to each sensor and the RIS is approximately fixed at each path segment. Thus, the coordinates of any point on the \( l \)th path segment are regarded as \( q_{U,l} \).

Define \( t_l \) as the flight time of the UAV along the \( l \)th path segment. From (1), the UAV’s propulsion power at the \( l \)th path segment can be expressed as follows:

\[
P_{p,l}(t_l) = P_0 \left( 1 + \frac{3 \delta_l^2}{U_{\text{up}}^2 t_l^2} \right) + P_1 \left( 1 + \frac{\delta_l^4}{4v_0^2 t_l^2} - \frac{\delta_l^2}{2v_0 t_l} \right)^{\frac{3}{2}}
+ \frac{1}{2} d_0 \rho s A \sum_{i \in \mathcal{L}_a} \frac{\delta_i^3}{t_i^4}.
\]  
(55)

Then, the total UAV energy consumption of one flight is given by

\[
E_U(q_U, t) = \sum_{l \in \mathcal{L}_a} t_l (P_1 + P_{p,l}(t_l))
\]  
(56)

where \( t = [t_1, \ldots, t_L]^T \).

B. Problem Formulation

Similar to the FHB protocol, when the UAV is at the \( l \)th path segment, we denote the phase shift of the \( m \)th reflecting element of the RIS by \( \theta_{m,l} \), and introduce the definitions \( \mathbf{q}_l = [e^{j \theta_{1,l}}, \ldots, e^{j \theta_{M,l}}]^T \) and \( \Phi_l = \text{diag} \{ \mathbf{q}_l \} \) for \( l \in \mathcal{L}_a \), which satisfies

\[
\theta_{m,l} \in [0, 2\pi), \quad m = 1, \ldots, M, \quad l \in \mathcal{L}_a.
\]  
(57)

Additionally, we denote the values of \( \beta_{k,q}, \beta_{d,k,q}, \) and \( \psi_{k,q} \), when the UAV is at the \( l \)th path segment by \( \beta_{l,i}, \beta_{d,l,i}, \) and \( \psi_{l,k,i} \), respectively. Hence, when the UAV is at the \( l \)th path segment, the expression of the expected received power \( \hat{P}_{k,l} \) at sensor \( k \) is the same as (17).

In this section, we propose to provide the required energy for all sensors with minimum energy consumption of the UAV, via jointly optimizing the trajectory \( q_U \), the flight time \( t \), and the reflection coefficient vectors \( \{\mathbf{q}_l\} \). The energy minimization problem is formulated as follows:

\[
\min_{q_U, t, \{\mathbf{q}_l\}} E_U(q_U, t)
\]  
(58a)

s.t.  
\[
\delta_l \leq \min \{\Delta_{\text{max}}, V_{\text{max}} t_l\}, \quad l \in \mathcal{L}_a
\]  
(58b)

\[
t_l \geq 0, \quad l \in \mathcal{L}_a
\]  
(58c)

\[
\eta \sum_{l \in \mathcal{L}_a} \eta \hat{P}_{k,l} \geq E_k^{\text{eq}}, \quad k = 1, \ldots, K
\]  
(14), (57).

(58d)

The main notations used in problem (58) are summarized in Table II. Note that in problem (58), the objective function \( E_U(q_U, t) \) and the constraints (57) and (58d) are nonconvex. Moreover, \( E_U(q_U, t) \) and constraint (58d) are not tractable due to the highly coupled variables. Fortunately, problem (58) has a similar form to problem (18). By extending the method in Section III, we propose an efficient algorithm for solving problem (58) in the following.

C. Optimizing the Trajectory \( q_U \) and Flight Time \( t \)

The proposed method for joint optimization of \( q_U \) and \( t \) under the FHB protocol in Section III-C provides an efficient algorithm framework for the PD protocol. By substituting (55) into (56), we can rewrite \( E_U(q_U, t) \) as follows:

\[
E_U(q_U, t) = \sum_{l \in \mathcal{L}_a} P_{p,l}(t_l) + \sum_{l \in \mathcal{L}_a} P_1 \left( 1 + \frac{\delta_l^4}{4v_0^2 t_l^2} - \frac{\delta_l^2}{2v_0 t_l} \right)^{\frac{3}{2}}
+ \sum_{l \in \mathcal{L}_a} P_0 \left( t_l + \frac{3 \delta_l^2}{U_{\text{up}}^2 t_l} \right) + \frac{1}{2} d_0 \rho s A \sum_{i \in \mathcal{L}_a} \frac{\delta_i^3}{t_i^4}.
\]  
(59)

Then, the subproblem for jointly optimizing the trajectory \( q_U \) and the flight time \( t \) under the PD protocol is formulated as follows:

\[
\min_{q_U, t} E_U(q_U, t)
\]  
(60a)

s.t.  
\[
(14), (58b)-(58d).
\]  
(60b)

Compared with the objective function of problem (19), that of problem (60) is much more complicated. In the following, we derive a lower bound for \( E_U(q_U, t) \) by applying the SCA method. To begin with, we introduce a set of slack variables \( x_l \geq 0 \) and let

\[
x_l^2 \geq \sqrt{t_l^4 + \frac{\delta_l^4}{4v_0^2} - \frac{\delta_l^2}{2v_0}}, \quad l \in \mathcal{L}_a.
\]  
(61)

It can be derived that

\[
\frac{t_l^4}{x_l^2} \leq x_l^2 + \frac{\delta_l^2}{v_0^2}, \quad l \in \mathcal{L}_a.
\]  
(62)
By taking the first-order Taylor expansion of the right-hand side of (62) w.r.t. $x$ and $\delta$, we have the following inequality:

$$x_i^2 + \delta_i^2 \geq 2x_i^0 x_i - x_i^2 + \frac{2}{v_0^2} \delta_i^2 \delta_i - \frac{1}{v_0^2} \delta_i^2, \quad l \in \mathcal{L}_a$$

(63)

where $x_i^2$ and $\delta_i^2$ are the value of $x_i$ and $\delta_i$ at the $n$th iteration, respectively. Then, to deal with the last term on the right hand side of (59), we introduce three sets of slack variables $\{\delta_i\}$, $\{z_i\}$ with

$$\delta_i \leq \delta_i, \quad l \in \mathcal{L}_a$$

(64)

$$\frac{\delta_i^3}{\nu_l^2} \leq \frac{\delta_i^2}{\delta_i}, \quad l \in \mathcal{L}_a$$

(65)

$$\frac{\delta_i^2}{\delta_i} \leq w_l, \quad l \in \mathcal{L}_a.$$  

(66)

Denote by $\delta_i^0$ the value of $\delta_i$ at the $n$th iteration. By utilizing the first-order Taylor expansion, we approximate the inequalities in (65) to

$$\frac{\delta_i^4}{\nu_l^2} \leq 2\delta_i^2 - \frac{\delta_i^2}{\nu_l^2}, \quad l \in \mathcal{L}_a.$$  

(67)

Then, a lower bound for $E_U(q_U, t)$ is obtained as follows:

$$\hat{E}_U(q_U, t) = \sum_{l \in \mathcal{L}_a} P_{tl} + \sum_{l \in \mathcal{L}_a} P_{sl} + \sum_{l \in \mathcal{L}_a} P_{st}(l + \frac{3\delta_i^2}{U_{l, p}^2})$$

$$+ \frac{1}{2} d_{l, p} a \sum_{l \in \mathcal{L}_a} w_l.$$  

(68)

By replacing $E_U(q_U, t)$ with $\hat{E}_U(q_U, t)$, we can formulate the problem at the $n$th SCA iteration as follows:

$$\min_{q_U, t \in \mathcal{L}_a} \hat{E}_U(q_U, t)$$

s.t. $\frac{\nu_l^2}{\nu_l^2} \leq 2\delta_i^2 - \frac{\delta_i^2}{\nu_l^2}, \quad l \in \mathcal{L}_a,$

$$\sum_{l \in \mathcal{L}_a}(U_{l, k, l} + U_{l, s, l}) \hat{\beta}_{k, l} + U_{l, s, l} \sqrt{\hat{\beta}_{k, l} \hat{\beta}_{k, l}} \geq 0, \quad l \in \mathcal{L}_a,$$  

(14), (58b)−(58d), (64), (66), (67).  

(69b)

Note that in problem (69), constraint (58d) is still nonconvex. We follow the similar strategy as in Section III-C to address this energy constraint. By taking the approximation in (20), we first transform constraint (58d) as follows:

$$\frac{\eta}{E_k} \sum_{l \in \mathcal{L}_a} P_{tl}(U_{l, k, l} + \sqrt{\hat{\beta}_{k, l} \hat{\beta}_{k, l}}) \geq 0, \quad k = 1, \ldots, K$$  

(70)

where $U_{l, k, l}$ and $\hat{\beta}_{k, l}$ are the value of $l$ at the $n$th iteration are given in (21)−(23), respectively. In addition, it can be readily verified that the inequalities in (25) and (26) still hold for $\hat{\beta}_{k, l}$ and $\beta_{k, l}$ under the PD protocol. Thus, (70) is replaced with the following constraints:

$$\frac{\eta}{E_k} \sum_{l \in \mathcal{L}_a} P_{tl}(U_{l, k, l} + \sqrt{\hat{\beta}_{k, l} \hat{\beta}_{k, l}}) \geq 0, \quad k = 1, \ldots, K$$  

(71)

where $\hat{\beta}_{k, l}$ and $\beta_{k, l}$ are slack variables. Furthermore, by introducing slack variables $\{\eta_{a, k, l}\}$ and $\{\eta_{d, k, l}\}$, we transform (71) into the following constraints:

$$\left(U_{l, k, l} + U_{l, s, l}\right)\eta_{a, k, l} + U_{l, s, l}^2 \eta_{d, k, l} \geq \frac{E_{k, t}^2}{\eta_{k, t}^2}$$  

(72)

$$l \in \mathcal{L}_a, \quad k = 1, \ldots, K$$  

(73)

Problem (77) is a convex problem that can be efficiently solved by the existing optimization tools, such as CVX.

D. Optimizing the Reflection Coefficient Vectors $\{\phi_i\}$

Similar to Section III-D, we take maximizing the minimum charged energy of all sensors as the objective of optimizing $\{\phi_i\}$. The corresponding optimization problem is given by

$$\max_{\{\phi_i\}, e}$$

s.t. $\frac{\eta}{E_k} \sum_{l \in \mathcal{L}_a} t_l \hat{\beta}_{k, l} \geq e, \quad k = 1, \ldots, K$  

(77a)

Note that problem (78) has the same form as problem (33) except for the value range of $l$. Therefore, by setting $L$ as the number of path segments and the index of $l$ as $\mathcal{L}_a$, the proposed Algorithm 1 in Section III-D can be directly applied for solving problem (78).

E. Algorithm Development

Based on the above discussions, we develop the SCA-MM method for solving problem (58), which is summarized in Algorithm 3. It can be found that Algorithm 3 follows a similar framework as Algorithm 2, where the optimal $\phi^{n+1}$ is calculated with Algorithm 1 in step 5. Compared with the FHB protocol, the PD protocol achieves higher flexibility in trajectory and flight time planning, which further reduces the energy consumption of the UAV.

Similar to Algorithm 2, the computational complexity of Algorithm 3 mainly lies in solving problem (77) in step 4 and calculating $\phi^{n+1}$ in step 5. Specifically, the complexity order of solving problem (77) is $O_{S4}^{N_k} = $
Algorithm 3 SCA-MM Algorithm Under the PD Protocol

Initialize: Initial the number of iterations as $n = 1$. Set feasible $\phi^1$, $\mathbf{q}_U^1$ and $\mathbf{t}^1$, the maximum number of iterations $n_{\text{max}}$, and smoothing-related factors $\mu$, $\mu_{\text{max}}$ and $\iota$.

1: repeat
2: Given $\mathbf{q}_U^n$, calculate $U_{1,k,l}^n$, $U_{2,k,l}^n$ and $U_{3,k,l}^n$ in (21)-(23);
3: Set $\{x^n_l\}$, $\{y^n_l\}$ and $\{e^n_{\phi,l}\}$ to hold the equalities in (61), (65) and (74), respectively;
4: Given $\phi^n$, calculate the optimal $\mathbf{q}_U^{n+1}$ and $\mathbf{t}^{n+1}$ by solving Problem (77);
5: Given $\mathbf{q}_U^{n+1}$ and $\mathbf{t}^{n+1}$, calculate the optimal $\phi^{n+1}$ with Algorithm 1;
6: Set $\mu \leftarrow \max\{\mu^t, \mu_{\text{max}}\}$ and $n \leftarrow n + 1$;
7: until $n \geq n_{\text{max}}$.

Fig. 2. Simulated RIS-assisted UAV-enabled WPT scenario and the initial trajectory of the UAV.

$O(\sqrt{SKL} + 2K + 11L(n^2KL^2 + nKL^3 + n^3))$, where $n = KL$. In addition, the complexity of calculating $\phi^{n+1}$ is of order $O_{\text{Alg.3}}^{\phi^{n+1}} = O(r_{\text{MM}}K(L^2M^2 + M^3))$. Hence, the overall complexity of Algorithm 3 is $O_{S4}^{\phi^{n+1}} + O_{S5}^{\phi^{n+1}}$.

V. SIMULATION RESULTS

In this section, extensive simulation results are presented to investigate the performance of the RIS-assisted UAV-enabled WPT system with the proposed algorithms.

A. Simulation Setup

Fig. 2 illustrates the simulation scenario, where $K = 5$ sensors are considered to be distributed in a semicircular area with a radius of 30 m. As shown in Fig. 2, the semicircle is divided into four equal parts by five radii, and there is a sensor on each radius. Specifically, sensor 1–4 are located on the circle, while sensor 5 is located at the midpoint of the radius. The RIS is deployed at the center of the semicircle with a height of $H_R = 10$ m. The flight height, maximum speed, and radiated power of the UAV are set as $H_U = 20$ m, $V_{\text{max}} = 30$ m/s, and $P_t = 40$ dBm, respectively. The initial and final locations are $q_1 = -35 + j0$ and $q_F = 35 + j0$. The parameters associated with UAV’s propulsion power are set to the same as in [31, Table 1], resulting in the MR speed of $v_{\text{mr}} = 18.3$ m/s. Unless otherwise specified, the simulation parameters are set as follows: the energy requirement for each sensor of $E_k^{\text{req}} = E_{\text{req}} = 0.2$ mJ, path-loss exponents of $\alpha_u = \alpha_c = 2.2$ and $\alpha_d = 2.6$, and Rician factors of $\kappa_i = \kappa_f = \kappa_d = 10$, $\lambda = 1$ m, $d = 0.5$ m, $\eta = 0.6$, $\Delta_{\text{max}} = 0.5$ m, $\epsilon_c = 10^{-6}$, $r_{\text{max}} = 10$, $\mu = 100$, $\mu_{\text{max}} = 1000$, $\iota = 1.07$, and $n_{\text{max}} = 60$.

In the following simulation results, the scheme with Algorithm 2 under the FHB protocol is denoted by FHB, and that with Algorithm 3 under the PD protocol is denoted by PD. For both protocols, the reflection coefficient vectors $\{\phi_i\}$ are initialized by setting $\theta_{m,l} = \pi$ $\forall m, l$. In FHB, five hovering locations ($L = 6$) are set with the same plane coordinates as the sensors, and the initialized trajectory $\mathbf{q}_U$ is illustrated by the yellow arrows in Fig. 2. In PD, the initial value of $\mathbf{q}_U$ is obtained by equally dividing each initialized path segment of FHB into portions with length not exceeding $(\Delta_{\text{max}}/1.8)$ ($L = 362$), and $\mathbf{t}$ is initialized by setting $\nu_l = v_{\text{mr}}$ for $l \in \mathcal{L}_a$.

B. Convergence of Proposed Algorithms

We first study the convergence of our proposed algorithms. For comparison, the following baseline schemes are also investigated.

1) FHB-SDR: To analyze the performance of our proposed Algorithm 1, this scheme solves problem (33) in PD by the SDR-based method with MOSEK solver [39] and $10^4$ Gaussian randomization operations.

2) FHB-noRIS and PD-noRIS: In these two schemes with no RIS deployed, the expected received power is given by $P_{k,l}^{\text{SnoRIS}} = \mathbb{E}(|P_l|^{2}g_{k,l}) = P_l|g_{k,l}|^2$. The corresponding energy minimization problems are solved by the methods we propose to solve problems (19) and (60).

3) FHB-2bit and PD-2bit: Due to hardware limitations, continuously tunable phase shifts are impractical to be implemented on the RIS. To investigate the system performance in practical scenarios, these two schemes with 2-bit resolution are considered, where each element of the optimal phase shifts $\{\theta_{m,l}\}$ obtained by Algorithms 2 and 3 is quantized as 0, $(\pi/2)$, $\pi$ or $(3\pi/2)$, and $\mathbf{q}_U$ and $\mathbf{t}$ are updated accordingly.

Fig. 3 plots the energy consumption of the UAV versus the number of iterations. It can be observed that FHB and PD converge in a few iterations. Additionally, thanks to the update strategies in Algorithms 2 and 3, there is no
obvious fluctuation. These demonstrate the effectiveness of our proposed algorithms in the joint optimization of the UA V’s trajectory, flight time, and the RIS’s reflection coefficients. Moreover, Fig. 3 shows that FHB outperforms FHB-SDR in both performance and convergence speed, which validates the advantages of Algorithm 1 in the passive beamforming design of the RIS for the entire flight.

C. Energy Saving Performance of RIS

Fig. 4 shows the energy consumption of the UA V versus the number of RIS reflecting elements. First, it is observed that the UA V energy consumption under the PD protocol is significantly lower than that under the FHB protocol. Due to the excellent flexibility in the planning of the UA V’s trajectory and flight time, the optimized solutions of the PD protocol achieve superior energy saving performance. Second, Fig. 4 shows that the energy consumption of the UA V decreases approximately linearly with the increase of $M$, which validates the efficiency of RIS on the energy saving. In addition, the performance comparison between FHB and FHB-SDR again verifies the advantages of Algorithm 1 over the SDR-based method. Compared with continuous phase shift schemes, it can also be observed that the performance loss of 2 bit schemes is slight.

D. Trajectory and Flight Time Planning of UAV

For two cases of the energy requirement $E_{k}^{\text{req}} = 0.2$ mJ and $E_{k}^{\text{req}} = 0.02$ mJ, Figs. 5 and 6 illustrate the optimized UA V’s trajectory and flight time, respectively. First, it can be observed from Fig. 5 that for both protocols, the UA V does not fly directly above the sensors. This is as expected since all sensors continually receive RF signals from the UA V and RIS during the flight. Radiating directly above each sensor leads to a longer flight distance, and thus, increases the power transmission time. As we mentioned in Section III-A, hovering is not the most energy efficient state for a rotor-wing UAV. Therefore, Fig. 6 shows that under the PD protocol, the UAV maintains a certain speed when it reaches an area favorable for power transmission. Additionally, in the scenario with lower sensor energy requirements, the UAV speed increases as the time required to radiate decreases, as expected. In Fig. 7, we compare the received power at sensors 1, 2, 3, and 5. Under the PD protocol, the received power at each sensor is larger than 0 regardless of the UA V’s location as expected, which maximizes the harvested energy. Furthermore, by allowing the UA V to radiate RF signals during its flight, the PD protocol enables greater flexibility for the joint design of UA V’s trajectory and flight time. From Fig. 5(a) and (b), FHB tends to reduce both the flight distance and the hovering time as the energy requirements decrease. For the PD protocol, its trend is interesting. From Fig. 7(b), when time duration is from 0 to 5 s, the received power for sensor 1 almost keeps stable at its largest value of $4 \times 10^{-6}$, which means the UA V may hover over sensor 1 in this time duration. However, for the
time duration from 5 to 10 s, the received power for sensor 2 first increases with the time and then decreases with the time, which implies that the UAV did not hover over sensor 2. The reason is that sensor 2 has already harvested enough energy as the UAV keeps transmitting the wireless energy during its flight.

VI. CONCLUSION

This article studied an energy-efficient UAV-enabled WPT system, where the received power of the RF signals at the sensors is enhanced by an RIS. We investigated the problems of providing the required energy for all sensors with minimum UAV energy consumption. Considering the FHB protocol for a simple scenario, the trajectory and hovering time of the UAV and the reflection coefficients of the RIS are jointly optimized. To solve this complex problem, we decoupled the variables by constructing two subproblems. By, respectively, utilizing the MM method and the SCA framework to solve the subproblems, an efficient iterative algorithm was proposed. For the general scenario, we formulated the energy minimization problem that jointly optimizes the UAV’s trajectory, flight time, and the RIS’s reflection coefficients by applying the PD protocol. A high-quality solution for this more challenging problem was obtained. Our simulation results demonstrated the effectiveness of the proposed algorithms and the energy-saving performance of RIS in UAV-enabled WPT systems.

APPENDIX A

PROOF OF THEOREM 1

By substituting (3), (4), and (9) into (10), it can be derived that

\[
\begin{align*}
E \left| g_{d,k,q} + g_{t,k,q}^H \Phi_q g_{e,k,q} \right|^2 &= |a_{0,k,q}|^2 + E \left| a_{1,k,q} \right|^2 \\
+ E \left| a_{2,k,q} \right|^2 + E \left| a_{3,k,q} \right|^2 + E \left| a_{4,k,q} \right|^2
\end{align*}
\]

(79)

where

\[
\begin{align*}
a_{0,k,q} &= \frac{\kappa_t \beta_{t,k}}{\kappa_t + 1} \left( \frac{\kappa_t \beta_{t,k}}{\kappa_t + 1} \right) \Phi_q g_{e,k,q} \\
&\quad + \frac{\kappa_d \beta_{d,k,q}}{\kappa_d + 1} \Phi_q g_{e,k,q} \\
a_{1,k,q} &= \frac{\beta_{d,k,q}}{\kappa_d + 1} \frac{\Phi_q g_{e,k,q}}{g_{NLoS}} \\
a_{2,k,q} &= \frac{\beta_{r,k}}{\kappa_r + 1} \left( \frac{\kappa_r \beta_{r,k}}{\kappa_r + 1} \right) \Phi_q g_{e,k,q} \\
a_{3,k,q} &= \frac{\kappa_t \beta_{t,k}}{\kappa_t + 1} \left( \frac{\kappa_t \beta_{t,k}}{\kappa_t + 1} \right) \Phi_q g_{e,k,q} \\
a_{4,k,q} &= \frac{\beta_{r,k}}{\kappa_r + 1} \left( \frac{\kappa_r \beta_{r,k}}{\kappa_r + 1} \right) \Phi_q g_{e,k,q} \\
\end{align*}
\]

(80)

It is readily to verify that \( E \left| g_{NLoS} (g_{r,k,q})^H \right| = I_M \), \( \Phi_q g_{NLoS} = I_M \), and \( (g_{NLoS})^H g_{NLoS} = M \). Hence, we have

\[
\begin{align*}
E \left| a_{2,k,q} \right|^2 &= E \left\{ \frac{\kappa_t \beta_{t,k}^2}{(\kappa_t + 1)(\kappa_t + 1)} \left( \frac{\kappa_t \beta_{t,k}^2}{(\kappa_t + 1)(\kappa_t + 1)} \right) \Phi_q g_{e,k,q} \right\} \\
&= \frac{\kappa_t \beta_{t,k}^2}{(\kappa_t + 1)(\kappa_t + 1)} \Phi_q g_{e,k,q}
\end{align*}
\]

(81)

Similarly, it can be derived that \( E \left| a_{1,k,q} \right|^2 = (\beta_{d,k,q}/\kappa_d + 1) \), \( E \left| a_{3,k,q} \right|^2 = (\beta_{r,k}/(\kappa_r + 1)(\kappa_r + 1)) \), and \( E \left| a_{4,k,q} \right|^2 = (M\beta_{r,k}/(\kappa_r + 1)(\kappa_r + 1)) \). Let us rewrite \( a_{0,k,q} \) as shown in (82), at the bottom of the next page. Then, with the definitions in (12) and (13), \( |a_{0,k,q}|^2 \) is derived as shown in (83), at the bottom of the next page. Finally, the expected received power \( \hat{P}_{k,q} = E[|P_{k,q}|^2] \) in (11) can be obtained by using (10) and (79). This thus completes the proof of Theorem 1.

APPENDIX B

PROOF OF THEOREM 2

Let \( \mathcal{R}_\phi = \{ \phi \mid \theta_m, \ell \in [0, 2\pi], \ m = 1, \ldots, M, \ l \in \mathcal{L}_b \} \) denote the feasible region of \( \phi \). Based on the MM method, \( f(\phi) \) is said to be minorized with \( \hat{f}(\phi | \phi^*) \) if the following conditions are satisfied.

(L1) \( \hat{f}(\phi | \phi^*) \) is continuous w.r.t. \( \phi \) and \( \phi^* \).
Denote by $\phi_{m,l}$ the $m$th element of $\phi$. In the following, we consider a relaxed condition (L3) by replacing $\mathcal{R}_\phi$ in (L3) with a relaxed feasible region $\mathcal{R}_\phi^{\text{relax}} \triangleq \{ \phi \mid \phi_{m,l} \leq 1, m = 1, \ldots, M, \; l \in L_l \}$. It will be shown that the conclusion also satisfies (L3). Specifically, we try to identify the expression of $C$ by setting $\tilde{f}(\phi | \phi')$ as the lower bound of $f(\phi)$ for each linear cut in any direction. By introducing an auxiliary variable $\gamma \in [0, 1]$ and letting $\phi = \phi' + \gamma(\phi^1 - \phi') \in \mathcal{R}_\phi^{\text{relax}}$, this sufficient condition is formulated as $j(\gamma) \geq J(\gamma)$, where

\[
\begin{align*}
J(\gamma) & \triangleq f(\phi') + 2\gamma \text{Re}\{\text{e}^H(\phi' - \phi')\} \\
& \quad + \gamma^2(\phi' - \phi')^H C (\phi^1 - \phi').
\end{align*}
\]

It can be readily verified that $j(0) = J(0)$. Denote by $\nabla_{\gamma} j(\gamma)$ the first-order derivative of $j(\gamma)$ w.r.t. $\gamma$. It can be derived that

\[
\nabla_{\gamma} j(\gamma) = \sum_{k=1}^{K} \tilde{g}_k(\gamma) \nabla_{\gamma} \tilde{h}_k(\gamma)
\]

where

\[
\tilde{h}_k(\gamma) \triangleq h_k(\phi' + \gamma(\phi^1 - \phi'))
\]

\[
\hat{g}_k(\gamma) \triangleq \frac{2}{\sum_{k=1}^{K} - \mu h_k(\gamma)}.
\]

By defining $\mathbf{e}_k \triangleq \mathbf{B}_k^H(\phi(\phi^1 - \phi')) + \mathbf{b}_k$ and $\tilde{\phi} \triangleq \phi^1 - \phi'$, we have $\nabla_{\gamma} \tilde{h}_k(\gamma) = 2\text{Re}\{\mathbf{e}_k^H \tilde{\phi}\}$. It is readily to verify that $\nabla_{\gamma} j(0) = \nabla_{\gamma} J(0)$. Therefore, a sufficient condition for $j(\gamma) \geq J(\gamma)$ is

\[
\nabla_{\gamma}^2 j(\gamma) \geq \nabla_{\gamma}^2 J(\gamma) \quad \forall \gamma \in [0, 1].
\]
The second-order derivative of $\tilde{h}_k(\gamma)$ is given by $\nabla^2_{\gamma} \tilde{h}_k(\gamma) = 2\tilde{h}_k(\gamma)^2$. Then, we have

$$\nabla^2_{\gamma} J(\gamma) = \sum_{k=1}^{K} \left( g_k(\gamma) \nabla^2_{\gamma} \tilde{h}_k(\gamma) - \mu g_k(\gamma) \nabla_{\gamma} \tilde{h}_k(\gamma) \right)^2 + \mu \left( \sum_{k=1}^{K} g_k(\gamma) \nabla_{\gamma} \tilde{h}_k(\gamma) \right)^2$$

$$= \begin{bmatrix} \phi & \phi^* \end{bmatrix} A \begin{bmatrix} \phi \\ \phi^* \end{bmatrix}$$

(94)

where

$$A = \sum_{k=1}^{K} g_k(\gamma) \left( \begin{bmatrix} B_k & 0 \\ 0 & B_k^T \end{bmatrix} - \mu \begin{bmatrix} e_k \\ e_k^* \end{bmatrix} \begin{bmatrix} e_k^T \\ e_k \end{bmatrix} \right)$$

$$+ \mu \left[ \sum_{k=1}^{K} g_k(\gamma) e_k \right] \left[ \sum_{k=1}^{K} g_k(\gamma) e_k^* \right]^T.$$  

(95)

In addition, the second-order derivative of $J(\gamma)$ can be derived as

$$\nabla^2_{\gamma} J(\gamma) = 2\tilde{h}_k(\gamma)^2 C \tilde{\phi} = \begin{bmatrix} \tilde{h}_k(\gamma)^2 \tilde{\phi}^T \end{bmatrix} \begin{bmatrix} C & 0 \\ 0 & C^T \end{bmatrix} \begin{bmatrix} \tilde{\phi} \\ \tilde{\phi}^* \end{bmatrix}.$$  

(96)

From (94) and (96), we have $A \geq \begin{bmatrix} C & 0 \\ 0 & C^T \end{bmatrix}$.

Let us define a set of auxiliary matrices $\{B_{k,l}\}$ that satisfies $B_k = \sum_{l \in L_k} B_{k,l}$ as follows:

$$B_{k,l} = \begin{bmatrix} 0_{(l-1)M} & A_{k,l} \\ 0_{(L-l-1)M} & 0_{l(l-1)M} \end{bmatrix}.$$  

(97)

It can be readily verified that $\text{rank}(B_{k,l}) = \text{rank}(A_{k,l}) = 1$. Therefore, we have $\text{rank}(B_k) \leq \sum_{l \in L_k} \text{rank}(B_{k,l}) = L - 1$ [40, eq. (1.6.4)]. Similarly, it can be proved that $B_k$ is low rank, thus $\lambda_{\min}(B_k) = 0$. To reduce the computational complexity of calculating $C$, we set $C = \alpha I$, where $\alpha$ is a simple lower bound of $\lambda_{\min}(A)$. To derive the expression of $\alpha$, we first obtain the inequalities in (98), shown at the top of the page, with the following lemmas.

(a1) $\lambda_{\min}(A) + \lambda_{\min}(B) \leq \lambda_{\min}(A + B)$, if $A$ and $B$ are Hermitian matrices [41].

(a2) $\lambda_{\max}(A) = \text{Tr}(A)$ and $\lambda_{\min}(A) = 0$, if $A$ is rank one [41].

(a3) $\sum_{m=1}^{M} a_m b_m \leq \max_{m=1}^{M} (b_m)$, if $a_m, b_m \geq 0$ and $\sum_{m=1}^{M} a_m = 1$ [42, Th. 30].

(a4) $\text{Tr}(AB) \leq \lambda_{\max}(A) \text{Tr}(B)$, if $A$ is positive semidefinite with maximum eigenvalue $\lambda_{\max}(A)$ and $B$ is positive semidefinite [41].

In addition, it is readily to verify the following.

(a5) $\max_{x = [x_1, \ldots, x_M]^T} \{ \text{Tr}(B_{k,l} x) \}$ and $\max_{x = [x_1, \ldots, x_M]^T} \{ \text{Tr}(B_{k,l} x) \}$ are the optimal solution and optimal value of the following problem for $x = [x_1, \ldots, x_M]^T$, respectively:

$$\max_{x} \text{Tr}(B_{k,l} x)$$

s.t. $|x_m| \leq 1 \ \forall m = 1, \ldots, M, \ l = 1, \ldots, L - 1.$

(99b)

Recall that $e_k \define B_k^H(\gamma(\phi^T - \phi) + \phi^* + b_k).$ The term $e_k^H e_k$ can be transformed as shown in (100), at the top of the page. By substituting (100) into (98), the expression of $\alpha$ in (99) is obtained. From (a5), it can be found that $\phi^* + \gamma(\phi^T - \phi) \in \mathcal{R}_\phi$ when the last equality in (100) holds. In addition, the expression for $\alpha$ is independent of $\gamma$. Hence, the proof is completed.

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