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Resource Allocation for Secure UAV-Assisted SWIPT Systems

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ABSTRACT The application of unmanned aerial vehicles (UAVs) is promising to improve the energy harvesting (EH) efficiency of simultaneous wireless and information and power transfer (SWIPT) system. However, the secure communications are challenging in UAV-assisted SWIPT systems due to the high probability of the existence of line-of-sight links between the UAV and eavesdroppers and the broadcast nature of SWIPT. In order to overcome it, a resource allocation problem is studied in an UAV-assisted SWIPT system, where the multiple eavesdroppers exist. The secrecy rate is maximized by jointly optimizing the trajectory and transmit power of the UAV. An alternative optimization algorithm is proposed to tackle the challenging non-convex problem. The simulation results demonstrate that our proposed resource allocation scheme outperforms other benchmark schemes in terms of the average secrecy rate. It is shown that our proposed algorithm is efficient to converge.

INDEX TERMS Unmanned aerial vehicles, physical layer security, SWIPT, resource allocation, energy harvesting.

I. INTRODUCTION

The rapid development of Internet of Things (IoT) enables users to enjoy diverse services with high quality of service, such as automatic drive [1]. It is facilitated by the unprecedented proliferation of mobile devices. However, since the battery capacities of those devices are finite, the time for enjoying those services is limit. It significantly decreases the users' quality of experience (QoE). Fortunately, energy harvesting (EH) is envisioned to be promising to overcome this issue. It enables users to harvest energy from the radio frequency (RF) signals. In the past few years, EH has attracted great attention from academic and industry [2], [5], [6], [8], [14]. As a category of EH, simultaneous wireless and information and power transfer (SWIPT) is attractive since it can simultaneously transmit information and energy to users [7]–[9]. In a typical SWIPT system, some users are used as information receivers (IRs) to decode information and others are used as energy receivers (ERs) to harvest energy from the RF signals.

Compared to the traditional EH techniques, such as solar or wind charging, SWIPT can provide stable and controllable energy to energy-limited devices. However, the EH efficiency is very limit due to the channel fading. In order to improve the EH efficiency, many methods have been studied, such as energy scheduling [5], energy waveform optimization [6] and multiple antenna techniques [7]. Recently, a technique for using unmanned aerial vehicles (UAVs) to assist SWIPT has been proposed. Due to the low cost, small size, flexibility and easy deployment, UAVs have been widely used in various fields, such as searching, rescuing, aerial photography and transportation. Recently, UAVs have also been applied to wireless communication systems [10]–[15]. Compared to the energy transmitter with a fixed position, UAV-assisted SWIPT systems have the high possibility of having short-distance line-of-sight (Los) links due to the high

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mobility of UAVs. Thus, the application of UAV-assisted SWIPT is promising.

A. RELATED WORK AND MOTIVATION

UAV-assisted wireless power transfer has been proposed in [16]–[21]. Yin *et al.* [16] studied the cooperative throughput maximization problem of UAV-assisted cooperative systems for both amplify-and-forward (AF) and decode-and-forward (DF) protocols. In such a cooperative communication system, the UAV servers as a mobile relay and its transmission capability depends on the harvesting energy from the source. Similar to [16], the resource allocation problem in an UAV-assisted netwotk that the UAV is used as an energy source for providing energy for multiple low-powered device-to-device (D2D) pairs was investigated in [17]. Xu [18], [19] investigated the sum-energy maximization of all ERs and the min-energy maximization problems with and without the maximum speed constraint, respectively. Unlike [16]–[19], Park *et al.* [20] investigated the minimum throughput maximization problem in integrated UAV and separated UAV wireless powered communication networks, respectively. Moreover, the resource allocation problem in an UAV-enabled wireless powered mobile edge computing system under both the partial and binary computation offloading modes was studied in [21].

On the other hand, although UAV-assisted SWIPT systems significantly improve the energy conversion efficiency, there may exist malicious ERs eavesdropping information sent by the UAV to the IR due to the broadcast and open nature of wireless channel. Thus, the security of UAV-assisted SWIPT systems is of crucial importance. To tackle this issue, physical layer security techniques have been proposed as viable anti-eavesdropping solutions [22]. Physical layer security techniques exploit the physical characteristics of wireless channels to achieve secure communications. Many methods for improving the secrecy rate have been proposed. Up to now, those methods include the idea of artificial noise (AN) [23]–[25], cooperative jamming (CJ) [26]–[28] and multiple antenna techniques. For the former, part of the transmit power is allocated to AN and while for the latter the friendly jammer transmits the jamming signal to confuse eavesdroppers. Specifically, Zhao *et al.* [23] proposed an AN-assisted interference alignment scheme by jointly optimizing the information transmit power and the coefficient of power splitting. Zhou *et al.* [24] investigated the problem of robust secure AN-aided beamforming and power splitting design both under the bounded channel state information (CSI) error model and the probabilistic CSI error mode. In [25], an AN-aided CJ scheme was proposed in a multiple-input single-output (MISO) non-orthogonal multiple access (NOMA) cognitive radio network under a non-linear EH model. In the literature based on the idea of CJ, in [26], the authors studied the secrecy rate maximization problem by jointly optimizing the power of the transmitter and jammer while satisfying the harvesting energy requirement of the ER. Zhang *et al.* [27] proposed a harvest-then-jam protocol with the assistance of a jammer to improve the secrecy performance in an orthogonal frequency division multiplexing (OFDM) system. Different from [26] and [27], Hoang *et al.* [28] investigated the physical layer security problem in cooperative EH networks consisting of a source, multiple intermediate EH nodes and a destination, where the EH nodes are selected as relays. It was shown that the security of the proposed system can be improved by increasing the number of intermediate nodes and increasing the signal-to-noise ratio (SNR).

Several works have been studied to exploit the physical layer security to improve the security of UAV-assisted wireless communication systems [29]–[33]. Zhang *et al.* [29] studied the average secrecy rate maximization problem of both uplink and downlink UAV communications with a destined node. Recently, UAV-aided jamming methods were considered to enhance the secrecy rate in UAV-aided communications. Specially, [30] employed the UAV as a jammer to enhance the secrecy performance between a transmitter and a receiver fixed at the ground with a ground eavesdropper. Different from [30], two UAVs are employed in [31]. One is used to communicate with the destination, and the other one is used to transmit jamming signal. To extend [31] into a general case, Lee *et al.* [32] considered a similar system with multiple legitimate users and TDMA protocol was also adopted to guarantee that confidential messages are intended to one scheduled user at each time slot. However, the locations of eavesdroppers are assumed to perfectly known in these works. Cui *et al.* [33] investigated the worst-case secrecy rate problem by jointly designing the robust trajectory and transmit power of the UAV with multiple eavesdroppers. However, these literatures have not considered SWIPT.

Different from the above works, we study a secure UAV-assisted SWIPT system in the presence of multiple eavesdroppers in this paper. The trajectory and transmit power of the UAV are jointly optimized to maximize the IR's secrecy rate while satisfying the minimum required energy of each ER, the UAV's power constraints, mobility constraints and initial and final location constraints. To the author's best knowledge, this is the first work that considers multiple eavesdroppers in UAV-assisted SWIPT systems.

B. CONTRIBUTIONS AND ORGANIZATION

In this paper, the resource allocation problem in an UAV-assisted SWIPT system consisting of an IR and multiple ERs is studied, where these ERs may eavesdrop the information that the UAV sends to the IR. The main contributions of this work are summarized as follows:

- The resource allocation problem in an UAV-assisted SWIPT system is formulated to maximize the secrecy rate of the IR, while taking into account the energy harvesting constraint of each ER, both UAV's average and maximum power constraints, mobility constraints and initial and final location constraints.
- The original problem is a non-convex problem, which is difficult to solve. To overcome this difficulty,

an alternative optimization algorithm is proposed, which divides the original problem into two sub-problems and those two sub-problems are separately solved. In the first sub-problem, the Lagrangian duality method is applied to obtain the optimal power for a given trajectory. In the second sub-problem, a slack variable is introduced in the objective function. Then, successive convex approximation (SCA) techniques are applied to approximate the problem into a convex optimization problem.

- The simulation results are presented to verify the performance of our proposed resource allocation algorithm. It is shown that the average secrecy rate obtained by using our proposed resource allocation algorithm is larger than that obtained by using two benchmark schemes. And the average secrecy rate increases with the maximum transmit power of the UAV.

The rest of the paper is organized as follows. Section II presents the system model and the secrecy rate maximization problem. The resource allocation algorithm is presented in Section III. Section IV presents the simulation results to verify our proposed algorithm and Section V concludes this paper.

Notation: In this paper, scalars are denoted by italic letters; vectors are denoted by bold-face lower-case letters and $\mathbb{R}^{M\times 1}$ denotes the space of M-dimensional real-valued vector. For a vector $\mathbf{a}$, $\|\mathbf{a}\|$ represents its Euclidean norm and $\mathbf{a}^T$ denotes its transpose.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. SYSTEM MODEL

As shown in Fig. 1, an UAV-assisted SWIPT system consisting of an IR and K ERs is considered, where a RF energy transmitter is mounted in the UAV. It is assumed that the IR and ERs have fixed locations and their locations are known to the UAV for its trajectory design, where the locations of IR and ERs can be detected by using an optical camera or synthetic aperture radar [34]. Without loss of generality, a 3D Cartesian coordinate system is considered, where the horizon

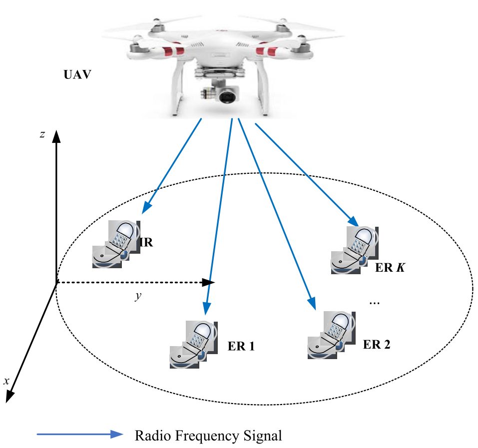

FIGURE 1. The system model.

coordinate of the IR is located at $\mathbf{w}_{IR} = [x_{IR}, y_{IR}] \in \mathbb{R}^{2\times 1}$, and each ER is located at $\mathbf{w}_{ER,k} = [x_{ER,k}, y_{ER,k}]^T \in \mathbb{R}^{2\times 1}$, $\forall k \in K$. The UAV is assumed to fly at a fixed altitude H above ground (H corresponds to the minimum altitude required for terrain or building avoidance). And the time-varying coordinate of the UAV for a finite time horizon with duration T is denoted by $\mathbf{q}(t) = [x(t), y(t)]^T \in \mathbb{R}^{2\times 1}$. In this paper, for simplicity, we only focus on the operation period, regardless of the taking-off and landing of the UAV. It is assumed that the UAV's initial and final locations are predetermined, whose horizon coordinates are denoted as $\mathbf{q}_0$, $\mathbf{q}_F$ and its maximum flying speed is denoted by V_{max}. To make the UAV trajectory feasible, the UAV also needs to subject to the maximum speed constraint. Thus, the UAV's initial and final location constraints and its maximum speed constraint can be expressed as

$$\mathbf{q}(0) = \mathbf{q}_0, \tag{1a}$$
$$\mathbf{q}(T) = \mathbf{q}_F, \tag{1b}$$
$$\|\dot{\mathbf{q}}(t)\| \le V_{max}, \forall t. \tag{1c}$$

For ease of exposition, the finite time T is discretized into N equal time slots, i.e., $t = n\delta_t$, $n = 1, \ldots, N$, where δ_t denotes the duration of each time slot and δ_t is chosen to be sufficiently small such that the UAV's location can be considered as approximately unchanged with each time slot. The constraints in (1) can be equivalently expressed as

$$\mathbf{q}[1] = \mathbf{q}_0, \tag{2a}$$
$$\mathbf{q}[N+1] = \mathbf{q}_F, \tag{2b}$$
$$\|\mathbf{q}[n+1] - \mathbf{q}[n]\|^2 \le D^2, \forall n, \tag{2c}$$

where $D = V_{max}\delta_t$ denotes the maximum flying distance in each slot. For simplicity, it is assumed that the communication channels from the UAV to the IR and ERs are dominated by line-of-sight (LOS) links and the Doppler effect caused by the UAV's mobility is assumed to be well compensated. And it has been also reported in [35] and [36] that the measurement results shows that the LoS model offers a good approximation for practical air-to-ground links. Therefore, the channel power gain from the UAV to the IR and ERs at time slot n follows the free-space path loss model, which can be expressed as

$$\begin{aligned} h_{IR}[n] &= \beta_0 d_{IR}^{-2}[n], \\ &= \frac{\beta_0}{\|\mathbf{q}[n] - \mathbf{w}_{IR}\|^2 + H^2}, \quad \forall n, \end{aligned} \tag{3a}$$
$$\begin{aligned} h_{ER,k}[n] &= \beta_0 d_{ER,k}^{-2}[n], \\ &= \frac{\beta_0}{\|\mathbf{q}[n] - \mathbf{w}_{ER,k}\|^2 + H^2}, \quad \forall n, k, \end{aligned} \tag{3b}$$

where β_0 denotes the channel power gain at the reference distance $d_0 = 1$ m, which depends on the carrier, frequency and antenna gain. $d_{IR}[n] = \sqrt{\|\mathbf{q}[n] - \mathbf{w}_{IR}\|^2 + H^2}$ is the distance between the UAV and IR at time slot n and $d_{ER,k}[n] = \sqrt{\|\mathbf{q}[n] - \mathbf{w}_{ER,k}\|^2 + H^2}$ is the distance between the UAV and the ER k at time slot n.

Let $p[n]$ denote the transmit power of the UAV in the nth time slot. Actually, $p[n]$ is usually subject to both the average and maximum power constraints denoted by $\overline{P}$ and P_{max}, respectively. The transmit power constraints can be expressed as

$$\frac{1}{N}\sum_{n=1}^{N} p[n] \le \overline{P}, \tag{4a}$$
$$0 \le p[n] \le P_{max}, \quad \forall n, \tag{4b}$$

It is assumed that $\overline{P} < P_{max}$. $\overline{P} < P_{max}$ is to make the constraints in (4) non-trivial. The harvesting energy of ER k in time slot n, denoted by $E_{ER,k}[n]$ is given as

$$\begin{aligned} E_{ER,k}[n] &= \eta p[n] h_{ER,k}[n], \\ &= \frac{\eta\beta_0 p[n]}{\|\mathbf{q}[n]-\mathbf{w}_{ER,k}[n]\|^2+H^2}, \quad \forall n,k, \end{aligned} \tag{5}$$

where $0 < \eta \le 1$ denotes the energy conversion efficiency at each ER. The achievable rate from the UAV to the IR in bits/second/Hertz (bps/Hz) in time slot n is given as

$$\begin{aligned} R_{IR}[n] &= \log_2\left(1+\frac{p[n]h_{IR}[n]}{\sigma^2}\right), \\ &= \log_2\left(1+\frac{\beta_0\, p[n]}{\sigma^2(\|\mathbf{q}[n]-\mathbf{w}_{IR}\|^2+H^2)}\right), \quad \forall n, \end{aligned} \tag{6}$$

where σ^2 is the noise power. Similarly, the achievable rate from the UAV to ER k in bps/Hz in time slot n is given as

$$\begin{aligned} R_{ER,k}[n] &= \log_2\left(1+\frac{p[n]h_{ER,k}[n]}{\sigma^2}\right), \\ &= \log_2\left(1+\frac{\beta_0\, p[n]}{\sigma^2(\|\mathbf{q}[n]-\mathbf{w}_{ER,k}[n]\|^2+H^2)}\right), \end{aligned} \tag{7}$$

The secrecy rate of the IR in time slot n, denoted by $R_{sec}[n]$ is given as

$$R_{sec}[n] = \left[R_{IR}[n] - \max_{k\in K} R_{ER,k}[n]\right]^+, \tag{8}$$

where $[x]^+ \triangleq \max\{x, 0\}$ and σ^2 is the noise power.

B. PROBLEM FORMULATION

In this paper, the aim of this work is to maximize the secrecy rate of the IR within a finite time T, while satisfying the energy harvesting constraint of each ER, both the UAV's average and maximum power constraints, mobility constraints and its initial and final location constraints. Let $\mathbf{p} \triangleq [p[1], ..., p[N]]^T$, $\mathbf{q} \triangleq [q[1], ..., q[N]]^T$. Thus, the secrecy rate maximization problem can be formulated as follows

$$\mathrm{P}_1: \max_{\mathbf{p},\mathbf{q}} \sum_{n=1}^{N}\left[R_{IR}[n] - \max_{k\in K} R_{ER,k}[n]\right]^+ \tag{9a}$$
$$\text{s.t. } C1: \sum_{n=1}^{N} E_{ER,k}[n] \ge Q, \quad \forall k, \tag{9b}$$
$$C2: \|\mathbf{q}[n+1]-\mathbf{q}[n]\|^2 \le D^2, \quad \forall n, \tag{9c}$$
$$C3: \mathbf{q}[1] = \mathbf{q}_0, \mathbf{q}[N+1] = \mathbf{q}_F, \tag{9d}$$
$$C4: \frac{1}{N}\sum_{n=1}^{N} p[n] \le \overline{P}, \tag{9e}$$
$$C5: 0 \le p[n] \le P_{max}, \quad \forall n, \tag{9f}$$

where the constant Q in $C1$ is the minimum required energy of each ER over the total time slots. The problem P_1 is difficult to solve due to the following reasons. Firstly, the operator $[\cdot]^+$ makes the objective function non-smooth at zero point. Secondly, even without $[\cdot]^+$, the original problem is still non-convex due to the coupling of multiple variables. We propose an efficient alternative algorithm for solving P_1 in Section III.

III. ALTERNATIVE OPTIMIZATION ALGORITHM

To tackle the non-smoothness of the objective function of problem P_1, the following lemma is presented.

Lemma 1: Problem P_1 is equivalent to problem $\mathrm{P}_{1.1}$ given as

$$\mathrm{P}_{1.1}: \max_{\mathbf{p},\mathbf{q}} \sum_{n=1}^{N}\left[R_{IR}[n] - \max_{k\in K} R_{ER,k}[n]\right] \tag{10a}$$
$$\text{s.t. } C1 - C5. \tag{10b}$$

Proof: Please refer to [29] and [33].

Although $\mathrm{P}_{1.1}$ resolves the non-smoothness of P_1, it is still non-convex due to the coupling of multiple variables. Thus we cannot use standard convex optimization techniques to tackle it. In order to solve the non-convex problem, a two-stage alternative optimization algorithm is proposed. First, the transmit power for a given UAV trajectory is optimized and then the UAV trajectory for a given transmit power is optimized. The details for the iterative algorithm are presented as follows.

A. OPTIMIZING TRANSMIT POWER

For a given UAV trajectory $\mathbf{q}$, the UAV transmit power optimization problem is given as

$$\mathrm{P}_2: \max_{\mathbf{p}} \sum_{n=1}^{N}\left[R_{IR}[n] - \max_{k\in K} R_{ER,k}[n]\right] \tag{11a}$$
$$\text{s.t. } C1, C4 \text{ and } C5. \tag{11b}$$

Let $a_n = \frac{\beta_0}{\sigma^2(\|\mathbf{q}[n]-\mathbf{w}_{IR}\|^2+H^2)}$, $b_{n,k} = \frac{\beta_0}{\sigma^2(\|\mathbf{q}[n]-\mathbf{w}_{ER,k}\|^2+H^2)}$. Because the UAV trajectory is given, one has

$$R_{sec}[n] = R_{IR}[n] - \max_{k\in K} R_{ER,k}[n], \tag{12a}$$
$$= \log_2(1+a_n p[n]) - \max\left[\log_2(1+b_{n,k}p[n])\right], \tag{12b}$$
$$= \log_2(1+a_n p[n]) - \log_2(1+b_{n,k^*}p[n]), \tag{12c}$$

where $b_{n,k^*} = arg\max_{k\in K} b_{n,k}$. P_2 is non-convex since the objective function is non-concave with respect to $p[n]$. It can be seen that when $a_n \le b_{n,k^*}$ the information sent by the UAV to the IR is eavesdropped by the ERs. In this case, the optimal power of the UAV denoted by $p^{opt}[n]$ is $p^{opt}[n] = 0$. It is easy to check that when $a_n > b_{n,k^*}$ the objective function of problem P_2 is concave with respect to $p[n]$ and P_2 is a convex optimization problem. Thus, for a given trajectory, the optimal power can be obtained by using the Lagrange duality method, which is given by the Theorem 1.

Theorem 1: For a given trajectory, the optimal power for maximizing the secrecy rate of the IR is given as

$$p^{opt}[n] = \begin{cases} \min([\hat{p}[n]]^+, P_{max}) & a_n > b_{n,k^*} \\ 0 & a_n \leq b_{n,k^*} \end{cases} \tag{13}$$

where

$$\hat{p}[n] = \sqrt{\left(\frac{1}{2b_{n,k^*}} - \frac{1}{2a_n}\right)^2 + \frac{1}{\ln 2\left(\frac{\mu}{N} - \sum_{k=1}^{K} c_{n,k}\right)}\left(\frac{1}{b_{n,k^*}} - \frac{1}{a_n}\right)} - \frac{1}{2b_{n,k^*}} - \frac{1}{2a_n}, \tag{14}$$

where $\mu \geq 0$ and $\lambda_k \geq 0$ are the dual variables associated with the constraints $C1$, $C4$ and $c_{n,k} = \frac{\eta\beta_0}{\|\mathbf{q}[n]-\mathbf{w}_{ER,k}\|^2+H^2}, \forall n, k$.

Proof: Please see Appendix.

Next, the subgradient method is used to update μ and λ_k, which are given by Lemma 2.

Lemma 2: The subgradient for updating the dual variables is given as

$$\mu(m+1) = [\mu(m) - \alpha(m)\Delta\mu(m)]^+, \tag{15a}$$

$$\lambda_k(m+1) = [\lambda_k(m) - \varepsilon(m)\Delta\lambda_k(m)]^+, \quad \forall k, \tag{15b}$$

where m denotes the iteration index; $\alpha(m)$ and $\varepsilon(m)$ are the iterative steps at the mth iteration. In (15), $\Delta\mu(m)$ and $\Delta\lambda_k(m)$ are the corresponding subgradients, which are given as

$$\Delta\mu(m) = \overline{P} - \frac{1}{N}\sum_{n=1}^{N} p[n], \tag{16a}$$

$$\Delta\lambda_k(m) = \sum_{n=1}^{N} \frac{\eta\beta_0\, p[n]}{\|\mathbf{q}[n] - \mathbf{w}_{ER,k}\|^2 + H^2} - Q, \quad \forall k. \tag{16b}$$

B. OPTIMIZING UAV TRAJECTORY

For a given transmit power $\mathbf{p}$, the UAV trajectory optimization problem is given as

$$P_3 : \max_{\mathbf{q}} \sum_{n=1}^{N}\left[R_{IR}[n] - \max_{k\in K} R_{ER,k}[n]\right] \tag{17a}$$

$$\text{s.t. } C1 - C3. \tag{17b}$$

Although the UAV transmit power is given, the problem P_3 is still a non-convex problem due to the objective function and the constraint $C1$. Thus, the problem is difficult to solve by using a standard convex optimization method. To tackle the difficulty, a slack variable $\tau[n] \geq 0$ is introduced in the objective function. Then P_3 can be equivalently expressed as

$$P_{3.1} : \max_{\mathbf{q},\tau[n]} \sum_{n=1}^{N} \tau[n] \tag{18a}$$

$$\text{s.t. } C1 - C3, \tag{18b}$$

$$\log_2\left(1 + \frac{\beta_0 p[n]}{\sigma^2(\|\mathbf{q}[n] - \mathbf{w}_{IR}\|^2 + H^2)}\right) - \log_2\left(1+\frac{\beta_0 p[n]}{\sigma^2(\|\mathbf{q}[n]-\mathbf{w}_{ER,k}[n]\|^2+H^2)}\right) \geq \tau[n], \quad \forall n, k, \tag{18c}$$

Note that $P_{3.1}$ is still a non-convex problem due to the constraints $C1$ and 18(c). To tackle the non-convexity of $C1$ and 18(c), SCA techniques are applied in each iteration. For constraint $C1$, although $C1$ is not a convex function with respect to $\mathbf{q}[n]$, it is a convex function with respect to $\|\mathbf{q}[n] - \mathbf{w}_{ER,k}\|^2$. Let $\mathbf{q}^m[n], \forall n$ denote the given UAV trajectory in the mth iteration. According to the theorem that the first-order Taylor expansion is globally lower-bounded of a convex function, the following inequality can be obtained

$$\begin{aligned} E_{ER,k}[n] &\geq -A_{ER,k}[n](\|\mathbf{q}[n] - \mathbf{w}_{ER,k}[n]\|^2 \\ &\quad - \|\mathbf{q}^m[n] - \mathbf{w}_{ER,k}[n]\|^2) + B_{ER,k}[n] \\ &\triangleq \hat{E}_{ER,k}[n], \quad \forall n, k, \end{aligned} \tag{19}$$

where the constants $A_{ER,k}[n]$ and $B_{ER,k}[n]$ are given as

$$A_{ER,k}[n] = \frac{\eta\beta_0\, p[n]}{(\|\mathbf{q}^m[n] - \mathbf{w}_{ER,k}[n]\|^2 + H^2)^2}, \quad \forall n, k, \tag{20a}$$

$$B_{ER,k}[n] = \frac{\eta\beta_0\, p[n]}{\|\mathbf{q}^m[n] - \mathbf{w}_{ER,k}[n]\|^2 + H^2}, \quad \forall n, k. \tag{20b}$$

For constraint 18(c), by introducing a slack $S_{ER,k}[n]$ such that $S_{ER,k}[n] \leq \|\mathbf{q}[n] - \mathbf{w}_{ER,k}[n]\|^2$, the problem $P_{3.1}$ can be reformulated as

$$P_{3.2} : \max_{\mathbf{q},\tau[n],S_{ER,k}[n]} \sum_{n=1}^{N} \tau[n] \tag{21a}$$

$$\text{s.t. } \sum_{n=1}^{N} \hat{E}_{ER,k}[n] \geq Q, \quad \forall k, \tag{21b}$$

$$\log_2\left(1 + \frac{\beta_0 p[n]}{\sigma^2(\|\mathbf{q}[n] - \mathbf{w}_{IR}\|^2 + H^2)}\right) - \log_2\left(1 + \frac{\beta_0 p[n]}{\sigma^2(S_{ER,k}[n] + H^2)}\right) \geq \tau[n], \quad \forall n, k, \tag{21c}$$

$$S_{ER,k}[n] \leq \|\mathbf{q}[n] - \mathbf{w}_{ER,k}[n]\|^2, \quad \forall n, k, \tag{21d}$$

$$C2 \text{ and } C3. \tag{21e}$$

$P_{3.2}$ is still a non-convex problem due to the constraints 21(c) and 21(d). Similar to constraint $C1$, it is easy to check that $\log_2\left(1 + \frac{\beta_0 p[n]}{\sigma^2(\|\mathbf{q}[n]-\mathbf{w}_{IR}\|^2+H^2)}\right)$ is a convex function with respect to $\|\mathbf{q}[n]-\mathbf{w}_{IR}\|^2$ and $\|\mathbf{q}[n]-\mathbf{w}_{ER,k}\|^2$ is a convex function with respect to $\mathbf{q}[n]$. Therefore, the following inequality can be obtained by using the first-order Taylor expansion

$$\begin{aligned} R_{IR}[n] \geq & -C_{IR}[n](\|\mathbf{q}[n]-\mathbf{w}_{IR}[n]\|^2 \\ & -\|\mathbf{q}^m[n]-\mathbf{w}_{IR}[n]\|^2)+D_{IR}[n] \\ \triangleq & \hat{R}_{IR}[n], \quad \forall n, \end{aligned} \tag{22a}$$

$$\begin{aligned} \|\mathbf{q}[n]-\mathbf{w}_{ER,k}\|^2 \geq & \|\mathbf{q}^m[n]-\mathbf{w}_{ER,k}\|^2 \\ & +2(\mathbf{q}^m[n]-\mathbf{w}_{ER,k})^T \\ & \times(\mathbf{q}[n]-\mathbf{q}^m[n]), \quad \forall n,k, \end{aligned} \tag{22b}$$

where

$$C_{IR}[n]=\frac{\beta_0\, p[n]\log_2 e}{(d_{IR}^m[n])^2\left(\sigma^2(d_{IR}^m[n])^2+\beta_0 p[n]\right)}, \quad \forall n, \tag{23a}$$

$$D_{IR}[n]=\log_2\left(1+\frac{\beta_0 p[n]}{\sigma^2(\|\mathbf{q}^m[n]-\mathbf{w}_{IR}\|^2+H^2)}\right), \quad \forall n, \tag{23b}$$

where $d_{IR}^m[n]=\sqrt{\|\mathbf{q}^m[n]-\mathbf{w}_{IR}\|^2+H^2}$ is the distance between the UAV and IR at time slot n in the mth iteration. As a result, P_3 can be approximately expressed as

$$\mathrm{P}_4: \max_{\mathbf{q},\tau[n],S_{ER,k}[n]} \sum_{n=1}^{N}\tau[n] \tag{24a}$$

$$\text{s.t.} \sum_{n=1}^{N}\hat{E}_{ER,k}[n]\geq Q, \quad \forall k, \tag{24b}$$

$$\hat{R}_{IR}[n]-\log_2\left(1+\frac{\beta_0 p[n]}{\sigma^2(S_{ER,k}[n]+H^2)}\right)\geq\tau[n], \quad \forall n,k, \tag{24c}$$

$$S_{ER,k}[n]\leq\|\mathbf{q}^m[n]-\mathbf{w}_{ER,k}\|^2 + 2(\mathbf{q}^m[n]-\mathbf{w}_{ER,k})^T(\mathbf{q}[n]-\mathbf{q}^m[n]), \quad \forall n,k, \tag{24d}$$

$$C2 \text{ and } C3. \tag{24e}$$

Since the left-hand side of (24c) is jointly concave with respect to $\mathbf{q}[n]$ and $S_{ER,k}[n]$, P_4 is a convex optimization problem, which can be solved efficiently by standard convex optimization tools such as CVX.

C. OVERALL ALGORITHM AND CONVERGENCE

Based on these results, an alternative optimization algorithm is summarized and the details for the algorithm can be seen in Table 1. The convergence analysis of our proposed iterative algorithm is given in the following. Let $R(\mathbf{p},\mathbf{q})$, $R_p(\mathbf{p},\mathbf{q})$, and $R_q(\mathbf{p},\mathbf{q})$ denote the objective value of $\mathrm{P}_{1.1}$, P_2 and P_4 for given $\mathbf{q}$, $\mathbf{p}$, respectively. Since the optimal solution of (11) is obtained for given $\mathbf{q}$, one has

$$\begin{aligned} R(\mathbf{p}^m,\mathbf{q}^m) &\leq R_p(\mathbf{p}^{m+1},\mathbf{q}^m), \\ &= R(\mathbf{p}^{m+1},\mathbf{q}^m), \end{aligned} \tag{25}$$

TABLE 1. The alternative optimization algorithm.

Algorithm 1: The alternative optimization for P_1

1: **Setting:**
  $T, N, Q, P_{max}, V_{max}, \mathbf{q}_0, \mathbf{q}_F$ and the tolerance error ξ.
2: **Initialization:**
  the iteration index $m=0$, $\mathbf{q}^m[n]$.
3: **Repeat :**
  calculate $p^{opt}[n]$ according to (13) with given $\mathbf{q}^m[n]$
  update μ, λ_k using the subgradient algorithm.
  solve P_4 using CVX for given $p^{opt}[n]$
  if $\Sigma_m-\Sigma_{m-1}\leq\xi$
    where $\Sigma_m=\sum_{n=1}^{N}\tau[n]$
    break;
  else
    Update the iterative number $m=m+1$;
  end if
 Until $\Sigma_m-\Sigma_{m-1}\leq\xi$
4: **Obtain solutions:**
  $p^{opt}[n]$ and $\mathbf{q}^{opt}[n]$

where $\mathbf{p}^{m+1}$ is the optimal transmit power of the UAV obtained according to (13). Since (19) and (22) are tight at the given local points, it follows

$$R(\mathbf{p}^{m+1},\mathbf{q}^m)=R_q(\mathbf{p}^{m+1},\mathbf{q}^m). \tag{26}$$

Then for given $\mathbf{p}^{m+1}$, it follows that

$$\begin{aligned} R_q(\mathbf{p}^{m+1},\mathbf{q}^m) &\overset{(a)}{\leq} R_q(\mathbf{p}^{m+1},\mathbf{q}^{m+1}), \\ &\overset{(b)}{\leq} R(\mathbf{p}^{m+1},\mathbf{q}^{m+1}), \end{aligned} \tag{27}$$

where (a) holds since problem P_4 is solved optimally with solution $\mathbf{p}^{m+1}$ and (b) holds since the objective value of P_4 is the lower bound of the origin problem. Based on (25)-(27), it can be obtained that

$$R(\mathbf{p}^m,\mathbf{q}^m)\leq R(\mathbf{p}^{m+1},\mathbf{q}^{m+1}), \tag{28}$$

(28) indicates that the objective value of $\mathrm{P}_{1.1}$ does not decrease after each iteration of our proposed iterative algorithm. Since the objective value of problem $\mathrm{P}_{1.1}$ upper bounded by a finite value, our proposed algorithm is guaranteed to converge.

We present the complexity analysis of our proposed algorithm as follows. The complexity of Algorithm 1 comes from three aspects. The first aspect is from the computation of the transmit power of the UAV. The second aspect is from the subgradient method for updating the dual variables. The third aspect is from the application of CVX for solving P_4. Let $L1$ and $L2$ denote the number of iterations required for the outer loop and the inner loop of Algorithm 1, respectively. Let ε denote the tolerance error for the subgradient method. According to the works in [37] and [38], the total complexity of Algorithm 1 is $\mathcal{O}[L_1(N+\frac{1}{\varepsilon^2}+L_2N^3)]$.

IV. SIMULATION RESULTS

In this section, simulation results are presented to compare the secrecy performance of our proposed trajectory and power control (denoted by "joint traj. opt. & pow. ctrl") algorithm with those obtained by using two benchmark schemes: best-effort trajectory design wit transmit power control (denoted by "best-effort traj. w/pow. ctrl") and trajectory optimization without power control (denoted by "traj. opt. w/o pow. ctrl"). Specially, in "best-effort traj. w/pow. ctrl " algorithm, the UAV trajectory is designed with the best-effort manner: the UAV firstly flies straight to above IR with the maximum speed and then hovers above IR and finally flies to the final location with the maximum speed by the last time slot. The transmit power is obtained by **Theorem 1**. In "traj. opt. w/o pow. ctrl" algorithm, the transmit power of the UAV is set as their corresponding average power in each time slot, i.e, $p[n] = \overline{P}$ and the UAV trajectory is obtained by solving P_4 until convergence. We set the initial trajectory for "joint traj. opt. & pow. ctrl" algorithm and "traj. opt. w/o pow. ctrl" algorithm generated by the "best-effort traj. w/pow. ctrl" algorithm.

An IR and two ERs are considered in the simulation, where their coordinates are set as $\mathbf{W}_{IR} = [10, 15]^T$, $\mathbf{W}_{ER1} = [5, 5]^T$ and $\mathbf{W}_{ER2} = [15, 5]^T$. The coordinates of UAV's initial and final location are set as $\mathbf{q}_0 = [0, 10]^T$ and $\mathbf{q}_F = [20, 10]^T$. The flying time of the UAV is $T = 20$ s and the length of each time slot is set as $\delta_t = 0.5$ s. The UAV is assumed to fly at a fixed altitude $H = 5$ m, the maximum speed is set as $V_{max} = 5$ m/s, the noise power is set as $\sigma^2 = -50$ dBm and the reference channel power gain is set as $\beta_0 = -30$ dBm. The maximum transmit power of the UAV is set as $P_{max} = 4\overline{P}$ and the tolerance error is set as $\xi = 10^{-4}$.

Fig. 2 shows the trajectories of the UAV achieved for $Q = 50$ μw and $Q = 80$ μw under different algorithms. The maximum transmit power of the UAV is set as $P_{max} = 2$ W. It is observed that the trajectories of the UAV obtained by "traj. opt. w/o pow. ctrl" algorithm and "joint traj. opt. & pow. ctrl" algorithm are similar while they are different from that obtained by "best-effort traj. w/pow. ctrl " algorithm. Specially, the UAV all firstly flies to a certain location and then hovers above this location as long as possible to achieve the maximum secrecy rate. Finally, the UAV flies to the final location with the maximum speed. The reason is that these hovering locations generally strike a balance between enhancing the legitimate channel and degrading the eavesdropping channel and hence maximize the secrecy rate in these cases. When the minimum required energy of each ER is $Q = 50$ μw, the UAV flies along the outermost trajectory in "traj. opt. w/o pow. ctrl" algorithm and it can be also observed that the UAV hovers at the same location for both "traj. opt. w/o pow. ctrl" algorithm and "joint traj. opt. & pow. ctrl" algorithm and the hovering location is in front of IR. The reason is that the UAV has sufficient time to fly to IR and then fly to the final location. It is also seen that when $Q = 80$ μw, the hovering location for both "traj. opt. w/o pow. ctrl" algorithm and "joint traj. opt. & pow. ctrl" algorithm are in the back of IR. This is because the UAV should fly close to the ERs in order to satisfy the minimum requirement energy of the ERs. Moreover, in "traj. opt. w/o pow. ctrl" algorithm, the trajectory of the UAV is inner than that obtained from the "joint traj. opt. & pow. ctrl" algorithm. The reason is that the transmit power in "traj. opt. w/o pow. ctrl" algorithm is not to be optimized. The trajectories obtained by "best-effort traj. w/pow. ctrl " algorithm are always the same regardless of the value of Q.

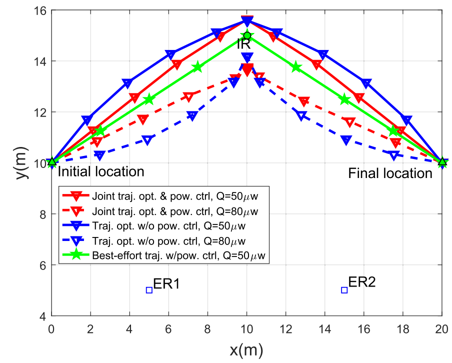

FIGURE 2. The trajectories of UAV under different algorithms.

Fig. 3 shows the average secrecy rate of the IR versus the maximum transmit power of the UAV under different algorithms. The minimum required energy is set as $Q = 30$ μw. It is seen that the average secrecy rate obtained by these three algorithms all increases with the maximum transmit power of the UAV. And it is also observed that the "joint traj. opt. & pow. ctrl" algorithm always has the highest secrecy rate while the "traj. opt. w/o pow. ctrl" algorithm always has the lowest secrecy rate. Moreover, the secrecy rate gap gradually

$$\begin{aligned} L(\Xi) &= \sum_{n=1}^{N}\Big(\log_2(1+a_n p[n]) - \log_2(1+b_{n,k^*}p[n])\Big) + \sum_{k=1}^{K}\lambda_k\Big(\sum_{n=1}^{N}\frac{\eta\beta_0\, p[n]}{\|\mathbf{q}[n]-\mathbf{w}_{ER,k}\|^2+H^2} - Q\Big) + \mu\Big(\overline{P} - \frac{1}{N}\sum_{n=1}^{N}p[n]\Big), \\ &= \sum_{n=1}^{N}\Big(\log_2(1+a_n p[n]) - \log_2(1+b_{n,k^*}p[n]) + \sum_{k=1}^{K}\frac{\eta\beta_0\lambda_k p[n]}{\|\mathbf{q}[n]-\mathbf{w}_{ER,k}\|^2+H^2} - \frac{\mu}{N}p[n]\Big) - \sum_{k=1}^{K}\lambda_k Q + \mu\overline{P}. \end{aligned} \tag{29}$$

$$L_n(\Xi) = \log_2(1+a_n p[n]) - \log_2(1+b_{n,k^*}p[n]) + \sum_{k=1}^{K}\frac{\eta\beta_0\lambda_k p[n]}{\|\mathbf{q}[n]-\mathbf{w}_{ER,k}\|^2+H^2} - \frac{\mu}{N}p[n]. \tag{32}$$

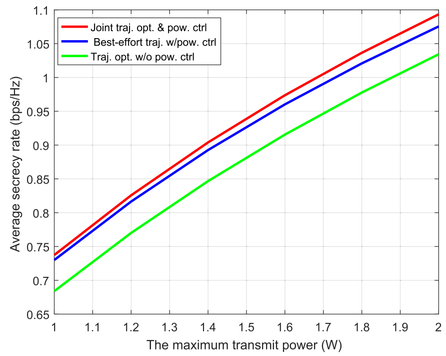

FIGURE 3. The average secrecy rate versus the maximum transmit power.

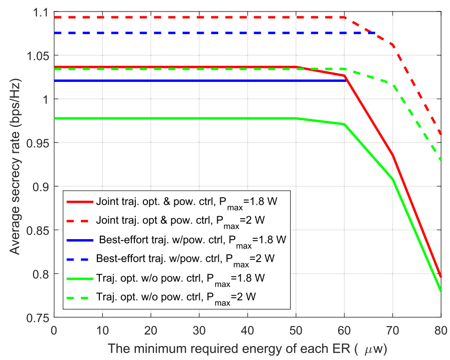

FIGURE 4. The average secrecy rate versus the minimum required energy of each ER.

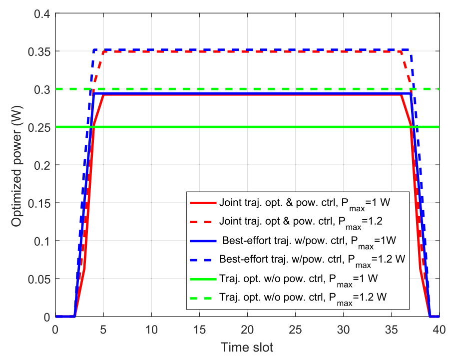

FIGURE 5. The optimized power versus the time slot.

increases between our proposed algorithm and the "best-effort traj. w/pow. ctrl " algorithm. This demonstrates that our proposed algorithm by jointly optimizing the trajectory and transmit power of the UAV is more efficient for improving the secrecy rate.

Fig. 4 shows the average secrecy rate of the IR versus the minimum required energy of each ER under different algorithms when the maximum transmit power is $P_{max} = 1.8$ W or $P_{max} = 2$ W. It is observed that the average secrecy rate obtained by "joint traj. opt. & pow. ctrl" algorithm and "traj. opt. w/o pow. ctrl" algorithm firstly is constant and then begins to decrease. The reason is that a higher transmit power is allocated to the ERs in order to satisfy the minimum energy harvesting requirement. The secrecy rate obtained by the "best-effort traj. w/pow. ctrl" algorithm is always constant.

Fig. 5 shows the optimized power versus the time slot when the maximum transmit power of the UAV is $P_{max} = 1$ W or

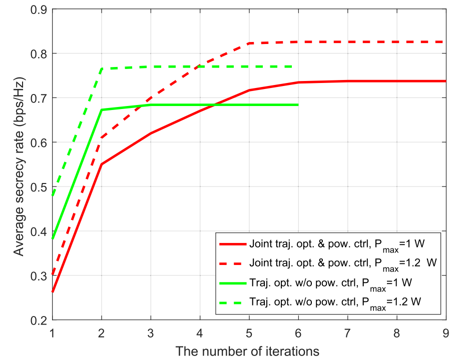

FIGURE 6. The average secrecy rate versus the number of iterations under different maximum transmit powers.

$P_{max} = 1.2$ W. The minimum required energy of each ER is set as $Q = 30\ \mu$w. It is observed that the optimized transmit power is symmetrically distributed and it is also seen that the optimized power firstly increases and then is constant and finally decreases to zero. This demonstrates that the transmit power increases as the UAV flies close to IR and then the transmit power is constant when the UAV hovers at a certain location and finally the transmit power decreases to zero as the UAV moves away from IR.

Fig. 6 shows the convergence of our proposed algorithm and "traj. opt. w/o pow. ctrl" algorithm. It can be seen that these two algorithms all only take several iterations to converge to a constant. It is also observed that the average secrecy rate obtained by these two algorithms firstly increases with the number of iterations and then converges to a constant with a few iterations. The "traj. opt. w/o pow. ctrl" algorithm converges faster than the proposed "joint traj. opt. & pow. ctrl" algorithm. The reason is that the transmit power in "traj. opt. w/o pow. ctrl" algorithm is not to be optimized.

V. CONCLUSION

In this paper, secure communications were studied in an UAV-assisted SWIPT system, where multiple eavesdroppers exist. The secrecy rate was maximized by jointly optimizing the trajectory and transmit power of the UAV. An alternative optimization algorithm was proposed to solve the challenging non-convex problem. Simulation results demonstrate that our proposed resource allocation scheme outperforms other benchmark schemes in terms of the average secrecy rate. It was shown that our proposed algorithm is efficient for convergence. In this paper, we considered that the locations of ERs are perfectly known. In our future work, we will consider more practical case that the locations of ERs are imperfectly known.

APPENDIX

PROOF OF THEOREM 1

The Lagrangian of problem P_2 related to the proof is given by (30) at the bottom of the previous page, Ξ denotes the set of all the optimization and dual variables. The Lagrangian dual function of P_2 can be expressed as

$$g(\mu, \lambda_k) = \max_{0 \le p[n] \le P_{max}} L(\Xi). \tag{30}$$

As a result, solving problem P_2 is equivalent to solve its dual problem, which is given as

$$\min_{\mu, \lambda_k} g(\mu, \lambda_k). \tag{31}$$

In the following, (30) can be solved with given dual variables. It is seen from (31) that the dual problem can be decomposed into N sub-problems and for each time slot, which is given by (32), as shown at the bottom of the Page 7. And where

$$L(\Xi) = \sum_{n=1}^{N} L_n(\Xi) - \sum_{k=1}^{K} \lambda_k Q + \mu \overline{P}. \tag{33}$$

Thus, the derivation of the Lagrangian of P_2 with respect to $p[n]$ is given as

$$\frac{\partial L_n(\Xi)}{\partial p[n]} = \frac{a_n}{ln2(1 + a_n p[n])} - \frac{b_{n,k^*}}{ln2(1 + b_{n,k^*} p[n])} + \sum_{k=1}^{K} \frac{\lambda_k \eta \beta_0}{\|\mathbf{q}[n] - \mathbf{w}_{ER,k}\|^2 + H^2} - \frac{\mu}{N}. \tag{34}$$

Then let the derivation be zero, we can obtain the optimal power $p^{opt}[n]$.

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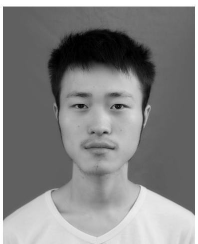

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