Resource allocation for UAV-assisted wireless powered D2D networks with flying and ground eavesdropping

Yin, C., Yang, H., Xiao, P., Chu, Z., & Garcia-Palacios, E. (2023). Resource allocation for UAV-assisted wireless powered D2D networks with flying and ground eavesdropping. *IEEE Wireless Communications Letters*, *27*(8), 2103-2107. https://doi.org/10.1109/LCOMM.2023.3289881

Published in:
IEEE Wireless Communications Letters

Document Version:
Peer reviewed version

This article has been accepted for publication in IEEE Communications Letters. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/LCOMM.2023.3289881

Resource Allocation for UAV-assisted wireless powered D2D networks with Flying and Ground Eavesdropping

Cheng Yin, Huiling Yang, Pei Xiao, *Senior Member, IEEE,* Zheng Chu, *Member, IEEE,* Emi Garcia-Palacios

***Abstract*—UAV-assisted wireless power transfer D2D networks have great potential to improve flexibility, spectrum efficiency and lifetime of future wireless networks. We consider an unmanned aerial vehicle (UAV)-assisted wireless powered device-to-device (D2D) wireless communication network in the presence of ground and flying eavesdroppers. We design optimization algorithms to allocate the resources of the network and maximize the secrecy energy efficiency (SEE) by optimizing energy harvesting time and power allocation. The effectiveness and viability of proposed algorithms are illustrated through numerical simulations.**

***Index Terms*—Physical layer security, energy harvesting, secrecy energy efficiency, UAV, D2D.**

I. Introduction

D2D communication networks provide direct communication connections between users without going through base stations and core networks, thus reducing the traffic load of the backhaul and expanding wireless coverage. However, due to the open environment of D2D transmissions, it is paramount to protect the network against information leakage and ensure the safety of D2D networks. The traditional technique to secure a system relies on cryptography which imposes high computational complexity and communication overhead. Therefore, it is impractical to be deployed for lightweight D2D devices [1]. Physical layer security (PLS) is an alternative technique to achieve secure communications with much lower complexity and overhead. The authors in [2] proposed non-orthogonal multiple access (NOMA) assisted secure computation offloading by cooperative jamming. The authors in [3] proposed power allocation algorithms to optimize secrecy throughput and energy efficiency (EE), enhancing network performance.

UAV-assisted communications also enhance the performance of D2D networks due to the light-of-sight (LoS) connections [4]. Another attractive deployment in UAV-assisted D2D networks is the application of energy harvesting. The UAV operates as an energy supplier for energy-constrained D2D devices to work continuously [5]. However, one of major challenges is that the drones have limited flight time and energy capacity, exhibiting the limitations of UAV-assisted networks. Therefore, it is imperative to design resource allocation algorithms to enhance EE for UAV-assisted D2D networks [6].

C. Yin, H. Yang, P. Xiao and Z. Chu are with the Institute for Communication Systems, University of Surrey, Guildford, GU2 7XH, UK. (email: c.yin@surrey.ac.uk, hy00562@surrey.ac.uk, p.xiao@surrey.ac.uk and andrew.chuzheng7@gmail.com).

E. Garcia is with the School of Electronics, Electrical Engineering and Computer Science, Queen's University Belfast, Belfast, BT7 1NN, UK. (e-mail: e.garcia@ee.qub.ac.uk).

Tackling the challenges of the resource allocation in UAV-assisted wireless power transfer networks has been attracting increasing attention [7]. Research in [8] proposed a cross-layer based resource allocation scheme in UAV-assisted wireless caching networks. Research in [9] investigated the resource power allocation problem by maximizing the average throughput for UAV-assisted and energy harvested D2D networks. Rather than optimizing average throughput [9], more recent research in [5] focused on optimizing the EE performance of UAV-assisted and energy harvesting powered D2D networks. However, all these studies in UAV-enabled energy harvested networks, e.g., [5], [8], [9], have not addressed the issue of information leakage for UAV-assisted D2D networks.

The above research gap in information leakage in UAV-assisted D2D networks motivates us to improve the secrecy performance against the wiretapping from eavesdroppers. Most existing research only considers ground eavesdropping in energy harvested D2D networks [6]. However, we also consider an aerial eavesdropper because it brings more threat to the wireless network due to the LoS connections. In this letter, we design novel resource allocation algorithms to combat ground and flying eavesdropping for UAV-assisted energy-harvested D2D networks by maximizing secrecy energy efficiency (SEE). Three novel optimization algorithms are proposed including a joint harvesting time and power allocation (JHTPA), and two near optimal secrecy resource allocation algorithms, namely, optimal energy harvesting time (OEHT) and optimal power allocation (OPA).

The contributions are listed as below:

- We design optimization algorithms to improve SEE under ground eavesdropping and aerial eavesdropping.
- A joint harvesting time and power allocation algorithm and two near optimal secrecy resource allocation algorithms are proposed.
- The simulation results provide comparisons of these three optimization algorithms.

II. System Model

We consider a system model including a UAV, energy constrained D2D transmitters $\mathrm{T}_{\{1,\ldots,I\}}$, D2D receivers $\mathrm{R}_{\{1,\ldots,I\}}$ in the presence of a ground eavesdropper (Ground E) or aerial eavesdropper (Flying E) who listen to the information between D2D transmitter pairs. The UAV provides wireless power to the energy-constrained D2D transmitters. T_i uses a duration of α to harvest energy from UAV, where α represents the energy harvesting time fraction, where $0 < \alpha < 1$. In addition,

This article has been accepted for publication in IEEE Communications Letters. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/LCOMM.2023.3289881

$(1-\alpha)$ is used for D2D information transmission. The energy harvested at T_i is given as

$$E_i = \eta P_m \alpha g_i, \tag{1}$$

where η represents the energy harvesting efficiency, P_m represents the UAV's maximum transmit power and g_i is the channel power gain of the wireless power transfer link from the drone to the ith transmitter. In practice, the harvested energy at T_i is used for information transmission, and it must satisfy the following energy constraint,

$$(1-\alpha)P_i \leq \alpha\eta P_m g_i, i \in I, \tag{2}$$

where P_i is the transmit power allocated to the ith transmitter. It is assumed that $\sqrt{h_{ii}}$, $\sqrt{h_{ji}}$ and $\sqrt{h_{ie}}$ denote the path gains, which are the D2D data link from the ith transmitter to the ith receiver, the interference link from the jth transmitter to the ith receiver, and the wiretap link from the ith transmitter to the E, respectively. Upon performing energy harvesting and information transmission, the signals received at R_i and E are

$$y_i = \sqrt{P_i h_{ii}} x_i + \sum_{j\neq i}^{I} \sqrt{P_j h_{ji}} x_j + n, \tag{3}$$

$$y_e = \sum_{i=1}^{I} \sqrt{h_{ie} P_i} x_i + n, \tag{4}$$

where $n \sim CN(0, \sigma^2)$ is the additive noise and x represents the transmitted symbol. For $\mathbf{p} = [P_i]_{i=1}^{I}$, the information rate (in nats) of the ith D2D transmission pair and from the ith D2D transmission to E are

$$f_i(\alpha, \mathbf{p}) = (1-\alpha)\ln\left(1 + \frac{P_i h_{ii}}{\sum_{j\neq i}^{I} h_{ji} P_j + \sigma^2}\right), \tag{5}$$

$$g_i(\alpha, \mathbf{p}) = (1-\alpha)\ln\left(1 + \frac{P_i h_{ie}}{\sum_{j\neq i}^{I} h_{je} P_j + \sigma^2}\right). \tag{6}$$

The total power consumption is given by

$$v(\alpha, \mathbf{p}) = \sum_{i=1}^{I} (1-\alpha)P_i + \eta P_m \alpha + P_{\mathbf{n}}, \tag{7}$$

where $P_{\mathbf{n}}$ represents the UAV's circuit non-transmit power. The secrecy rate of the transmission from T_i to R_i is

$$\max\left\{f_i(\alpha, \mathbf{p}) - g_i(\alpha, \mathbf{p}), 0\right\}. \tag{8}$$

In this letter, we consider the SEE optimization under the energy causality and quality-of-service (QoS) constraints of the considered networks, formulated as

$$\max \phi(\alpha, \mathbf{p}) = \frac{\sum_{i=1}^{I}[f_i(\alpha, \mathbf{p}) - g_i(\alpha, \mathbf{p})]}{v(\alpha, \mathbf{p})}, \tag{9a}$$

$$s.t.\ (2), \tag{9b}$$

$$0 \leq \alpha \leq 1, \tag{9c}$$

$$f_i(\alpha, \mathbf{p}) \geq r_{min}, \tag{9d}$$

where r_{min} represents the QoS constraint of the considered D2D networks. It is shown that the objective function in (9a) is nonconcave. In addition, the constraint in (9d) is nonlinear. Thus, this is considered as a nonconvex optimization problem.

III. Joint Harvesting time and power allocation for SEE optimization (JHTPA)

We propose an algorithm to optimize SEE by jointly optimizing α and $\mathbf{p}$ parameters. We first change the variable

$$1-\alpha = \frac{1}{\theta}, \tag{10}$$

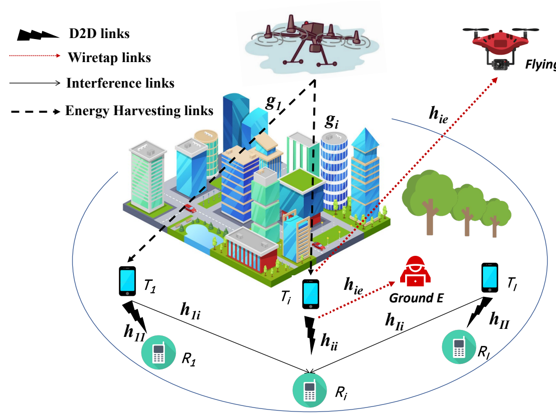

Fig. 1: UAV-assisted wireless energy harvested D2D communications under ground and flying eavesdropping.

with the following constraint

$$\theta > 1. \tag{11}$$

The SEE optimization problem is rewritten as

$$\max \phi(\theta, \mathbf{p}) = \frac{\sum_{i=1}^{I}[f_i(\theta, \mathbf{p}) - g_i(\theta, \mathbf{p})]}{v(\theta, \mathbf{p})}, \tag{12a}$$

$$s.t.\ (11), \tag{12b}$$

$$P_i \leq (\theta - 1)\eta P_m g_i, \tag{12c}$$

$$\frac{1}{\theta}\ln\left(1 + \frac{P_i h_{ii}}{\sum_{j\neq i}^{I} h_{ji} P_j + \sigma^2}\right) \geq r_{min}, \tag{12d}$$

where

$$v(\theta, \mathbf{p}) = \sum_{i=1}^{I} P_i/\theta + (1 - 1/\theta)\eta P_m + P_{\mathbf{n}}. \tag{13}$$

We utilize the following logarithmic inequality for the non-convex optimization problem [3]

$$\begin{aligned} \frac{\ln(1+\frac{1}{xy})}{z} \geq{}& \frac{2}{\bar{z}}\ln\left(1+\frac{1}{\bar{x}\bar{y}}\right) + \frac{2}{\bar{z}(\bar{x}\bar{y}+1)} - \frac{1}{\bar{z}\bar{x}(\bar{x}\bar{y})+1}x \\ &- \frac{1}{\bar{z}\bar{y}(\bar{x}\bar{y}+1)}y - \frac{\ln(1+\frac{1}{\bar{x}\bar{y}})}{\bar{z}^2}z, \\ &\forall z > 0, \bar{z} > 0, x > 0, \bar{x} > 0, y > 0, \bar{y} > 0, \end{aligned} \tag{14}$$

for $x = 1/h_{ii}P_i$, $y = \sum_{j\neq i}^{I} h_{ji}P_j + \sigma^2$, $z = \theta$, $\bar{x} = 1/h_{ii}P_i^{(k)}$, $\bar{y} = \sum_{j\neq i}^{I} h_{ji}P_j^{(k)} + \sigma^2$, $\bar{z} = \theta^{(k)}$, $\bar{x}, \bar{y}, \bar{z}$ represent the values of x, y, z after the kth iteration and it could be arrived as [3]

$$f_i(\theta, \mathbf{p}) \geq f_i^{(k)}(\theta, \mathbf{p}), \tag{15}$$

where

$$\begin{aligned} f_i^{(k)}(\theta, \mathbf{p}) ={}& \frac{2}{z^{(k)}}\ln\left(1+\frac{1}{x^{(k)}y^{(k)}}\right) + \frac{2}{z^{(k)}(x^{(k)}y^{(k)}+1)} \\ &- \frac{1}{z^{(k)}x^{(k)}(x^{(k)}y^{(k)})+1}x - \frac{1}{z^{(k)}y^{(k)}(x^{(k)}y^{(k)}+1)}y \\ &- \frac{\ln(1+\frac{1}{x^{(k)}y^{(k)}})}{{z^{(k)}}^2}z. \end{aligned} \tag{16}$$

This article has been accepted for publication in IEEE Communications Letters. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/LCOMM.2023.3289881

Similarly, $g_i(\mathbf{p},\theta)$ can be approximated by the logarithmic inequality [3]

$$\frac{\ln(1+x)}{z} \leq -2\frac{\alpha-\ln(1+\bar{x})}{\bar{z}} - \frac{\bar{x}}{\bar{z}(1+\bar{x})} + \frac{x}{\bar{z}(1+\bar{x})} + \frac{\alpha-\ln(1+\bar{x})}{\bar{z}^2}z + \frac{\alpha}{z}, \tag{17}$$

for $x = \frac{P_i h_{ie}}{\sum_{j\neq i}^I h_{je}P_j+\sigma^2}$, $z=\theta$, $\bar{x} = \frac{P_i^{(k)} h_{ie}}{\sum_{j\neq i}^I h_{je}P_j^{(k)}+\sigma^2}$, $\bar{z} = \theta^{(k)}$, $\alpha = 1+\ln 2$, and achieves

$$g_i(\theta,\mathbf{p}) \leq g_i^{(k)}(\theta,\mathbf{p}), \tag{18}$$

where

$$g_i^{(k)}(\theta,\mathbf{p}) = -2\frac{\alpha-\ln(1+x^{(k)})}{z^{(k)}} - \frac{x^{(k)}}{z^{(k)}(1+x^{(k)})} + \frac{x}{z^{(k)}(1+x^{(k)})} + \frac{\alpha-\ln(1+x^{(k)})}{z^{2(k)}}z + \frac{\alpha}{z}. \tag{19}$$

We initialize feasible points $(\theta^{(0)},\mathbf{p}^{(0)})$ for the convex constraints, and at k-th iteration we tackle the optimization problem in (20) and compute the following iterative values $(\theta^{(k+1)},\mathbf{p}^{(k+1)})$. As (20) includes $(I+1)$ decision variables and $(I+1)$ linear constraints, the computational complexity is $\mathcal{O}\left[(I+1)^{4.5}+(I+1)^{3.5}\right]$ [3].

$$\max \phi^{(k)}(\theta,\mathbf{p}) = \frac{\sum_{i=1}^I [f_i(\theta^{(k)},\mathbf{p}^{(k)}) - g_i(\theta^{(k)},\mathbf{p}^{(k)})]}{v(\theta^{(k)},\mathbf{p}^{(k)})}, \quad s.t. (11), (12c), (12d). \tag{20}$$

We can find that $\phi^{(k)}(\theta^{(k+1)},\mathbf{p}^{(k+1)}) > \phi^{(k)}(\theta^{(k)},\mathbf{p}^{(k)})$ if $(\theta^{(k+1)},\mathbf{p}^{(k+1)}) \neq (\theta^{(k)},\mathbf{p}^{(k)})$, as the former points are the optimal values of (20) while the latter points are the feasible values [3]. Hence, we can obtain

$$\phi(\theta^{(k+1)},\mathbf{p}^{(k+1)}) \geq \phi^{(k)}(\theta^{(k+1)},\mathbf{p}^{(k+1)}) > \phi^{(k)}(\theta^{(k)},\mathbf{p}^{(k)}) = \phi(\theta^{(k)},\mathbf{p}^{(k)}), \tag{21}$$

where $\{\theta^{(k)},\mathbf{p}^{(k)}\}$ are enhanced values that converges at least to a locally optimal solutions of the problems that satisfy the first order necessary optimality condition [10, Proposition 1]. We summarize the optimization algorithm as a path-following computational procedure in Algorithm 1.

Algorithm 1 Joint Energy Harvesting Time and Power Allocation Optimization Algorithm for Maximizing SEE

Initialization: Select initial values $\theta^{(0)}$ and $\mathbf{p}^{(0)}$ satisfying the constraints by random search. Compute the values of the objectives in (12a) at $\mathbf{p}^{(0)}$ and $\theta^{(0)}$, as $R^{(k)}$. Set $k=0$ and the tolerance ϵ_{tol}=10^{-2}.

repeat
- $k=k+1$.
- Solve optimization problem (21) and generate $\theta^{(k)}$, $\mathbf{p}^{(k)}$.
- Compute $R^{(k)}$ and obtain the value for (12a) at $\theta^{(k)}$, $\mathbf{p}^{(k)}$.

until $\frac{R^{(k)}-R^{(k-1)}}{R^{(k-1)}} \leq \epsilon_{tol}$.

IV. Near-Optimal Secrecy Resource Allocation Algorithms

We present two low-complexity near-optimal resource allocation algorithms, namely, OEHT and OPA, comparing them with JHTPA in SEE performance and convergence times.

A. Optimal Energy Harvesting Time (OEHT)

The OEHT algorithm optimizes the energy harvesting time with the maximum harvested power at T_i. The maximum harvested power at D2D networks is

$$P_i = (\theta-1)\eta P_m g_i. \tag{22}$$

Then, the maxi-min sum-rate problem is rewritten as,

$$\max \phi(\theta) = \min_{i=1,\dots,I} [f_i(\theta) - g_i(\theta)], s.t. (11) \tag{23}$$

where

$$f_i(\theta) = \frac{1}{\theta}\ln\left(1+\frac{(\theta-1)g_i h_{ii}}{(\theta-1)\sum_{j\neq i}^I h_{ji}g_j + \frac{\sigma^2}{\eta P_m}}\right), \tag{24}$$

$$g_i(\theta) = \frac{1}{\theta}\ln\left(1+\frac{(\theta-1)g_i h_{ie}}{\sum_{j\neq i}^I h_{je}(\theta-1)g_j + \frac{\sigma^2}{\eta P_m}}\right), \tag{25}$$

where $f_i(\theta)$ in objective function can be approximated with the help of the inequality in (14) for $x = 1/(\theta-1)h_{ii}g_i$, $y = \sum_{j\neq i}^I h_{ji}(\theta-1)g_j + \sigma^2/\eta P_m$, $z=\theta$, $\bar{x} = x^{(k)} = 1/(\theta^{(k)}-1)h_{ii}g_i$, $\bar{y} = y^{(k)} = \sum_{j\neq i}^I h_{ji}(\theta^{(k)}-1)g_j + \sigma^2/\eta P_m$, $\bar{z} = z^{(k)} = \theta^{(k)}$ and we have

$$f_i(\theta) \geq f_i^{(k)}(\theta), \tag{26}$$

where $f_i^{(k)}(\theta)$ can be found in (16). On the other hand, $g_i(\theta)$ is approximated with the help of (17) for $z=\theta$, $x = \frac{(\theta-1)g_i h_{ie}}{\sum_{j\neq i} h_{je}(\theta-1)g_j+\sigma^2/\eta P_m}$, $\bar{x} = \frac{(\theta^{(k)}-1)g_i h_{ie}}{\sum_{j\neq i} h_{je}(\theta^{(k)}-1)g_j+\sigma^2/\eta P_m}$, $\bar{z} = z^{(k)} = \theta^{(k)}$. Then, we use the inequality,

$$x \leq \frac{1}{2}(\frac{x^2}{\bar{x}}+\bar{x}), \forall x>0, \bar{x}>0, \tag{27}$$

to obtain $x = \frac{0.5 g_i h_{ie}\left[(\theta-1)^2/(\bar{\theta}-1)\right]+0.5 g_i h_{ie}(\bar{\theta}-1)}{\sum_{j\neq i} h_{je}(\theta-1)g_j+\sigma^2/\eta P_m}$ and we have

$$g_i(\theta) \leq g_i^{(k)}(\theta), \tag{28}$$

where $g_i^{(k)}(\theta)$ is in (19). At the k-th iteration, the maxi-min optimization is converged to compute the next iterated value,

$$\max \phi^{(k)}(\theta) = \min_{i=1,\dots,I} [f_i^{(k)}(\theta) - g_i^{(k)}(\theta)], s.t. (11). \tag{29}$$

Then, we obtain the optimal value θ_{sol} and SEE is

$$\phi(\theta_{sol}) = \frac{\sum_{i=1}^I [f_i(\theta_{sol}) - g_i(\theta_{sol})]}{v(\theta_{sol})}, \tag{30}$$

where $v(\theta_{sol}) = (1-\frac{1}{\theta_{sol}})\eta P_m(\sum_{i=1}^I P_i+1) + P_{\mathbf{n}}$.

B. Optimal Power Allocation (OPA)

The OPA algorithm is designed to allocate the power resources to maximize the SEE in (9). The energy harvesting time is $1-\alpha = 1/\theta_{fix}$, where $\theta_{fix} > 1$. Therefore, the optimization problem is rewritten as

$$\max \phi(\theta_{fix},\mathbf{p}) = \frac{\sum_{i=1}^I [f_i(\theta_{fix},\mathbf{p}) - g_i(\theta_{fix},\mathbf{p})]}{v(\theta_{fix},\mathbf{p})}, \tag{31a}$$

$$s.t. P_i \leq (\theta_{fix}-1)\eta P_m g_i, \tag{31b}$$

$$\ln\left(1+\frac{P_i h_{ii}}{\sum_{j\neq i}^I h_{ji}P_j+\sigma^2}\right) \geq r_{min}\theta_{fix}, \tag{31c}$$

where

$$v(\theta_{fix},\mathbf{p}) = \sum_{i=1}^I P_i/\theta_{fix} + (1-1/\theta_{fix})\eta P_m + P_{\mathbf{n}}. \tag{32}$$

Then, we utilize the following inequality for $f_i(\theta_{fix},\mathbf{p})$ in the objective function (31a)

$$\ln(1+\frac{1}{xy}) \geq \ln(1+\frac{1}{\bar{x}\bar{y}}) + \frac{1/\bar{x}\bar{y}}{1+1/\bar{x}\bar{y}}(2-\frac{x}{\bar{x}}-\frac{y}{\bar{y}}), \tag{33}$$

This article has been accepted for publication in IEEE Communications Letters. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/LCOMM.2023.3289881

for $x = 1/P_i h_{ii}$, $y = \sum_{j\neq 1}^{M} h_{ji}P_j + \sigma^2$, $\bar{x} = 1/P_i^{(k)} h_{ii}$, $\bar{y} = \sum_{j\neq 1}^{M} h_{ji}P_j^{(k)} + \sigma^2$ and thus we have

$$f_i(\theta_{fix}, \mathbf{p}) \geq f_i^{(k)}(\theta_{fix}, \mathbf{p}), \tag{34}$$

and $f_i^{(k)}(\theta_{fix}, \mathbf{p})$ is given in (16).

Similarly, we can apply the following inequality for $g_i(\theta_{fix}, \mathbf{p})$ in the objective function (31a)

$$\ln(1+\frac{x}{y}) \leq \ln(1+\frac{\bar{x}}{\bar{y}}) + \frac{1}{1+\bar{x}/\bar{y}}\left(\frac{0.5\left(\frac{x^2}{\bar{x}}+\bar{x}\right)}{y} - \frac{\bar{x}}{\bar{y}}\right), \tag{35}$$

for $x = P_i h_{ie}$, $y = \sum_{j\neq i} h_{je}P_j + \sigma^2$, $\bar{x} = P_i^{(k)} h_{ie}$ and $\bar{y} = \sum_{j\neq i} h_{je}P_j^{(k)} + \sigma^2$, and thus we have

$$g_i(\theta_{fix}, \mathbf{p}) \leq g_i^{(k)}(\theta_{fix}, \mathbf{p}), \tag{36}$$

where $g_i^{(k)}(\theta_{fix}, \mathbf{p})$ is defined in (19). Obtaining the feasible values $\mathbf{p}^{(k)}$, we have

$$\max \phi^{(k)}(\theta_{fix}, \mathbf{p}) = \frac{\sum_{i=1}^{I}[f_i(\theta_{fix}, \mathbf{p}^{(k)}) - g_i(\theta_{fix}, \mathbf{p}^{(k)})]}{v(\theta_{fix}, \mathbf{p}^{(k)})}, \tag{37}$$

and the optimization problem is solved until the convergence of $\frac{R^{(k)}-R^{(k-1)}}{R^{(k-1)}} \leq \epsilon_{tol}$, where $R^{(k)}$ is the value of objective at θ_{fix}, $\mathbf{p}^{(k)}$.

V. Simulation Results

We evaluate the secrecy performance of the considered network in MatLab with the CVX tool box. The computational platform is a desktop computer with an AMD Ryzen 5 5600G, CPU @3.9GHz and 16GB memory. We consider a central unit to exchange transmission information of D2D networks. The energy supplier UAV is deployed at the central point of a circle coverage communication network. The radius of the circle is 800m and the flying height H_U of the UAV is assumed to be 100m. The D2D transmission pairs are positioned at random. The largest distance between each D2D pair is 50m. We examine the secrecy performance under two eavesdropping scenarios: 1) E is randomly located on the ground; 2) E is a drone with flying height H_E between 100m and 500m.

The ground-to-ground channel power gain h_{ii} between D2D pairs is modeled as [5]

$$h_{ii} = \beta\rho^2 D^{-\alpha}, \tag{38}$$

where β represents the channel power gain at the reference distance d_0, ρ follows an exponentially distributed random variable with unit mean. In addition, D denotes the distance between D2D transmission pairs and α is the pathloss of the ground-to-ground channel. The channel power gain between the ground E and T$_i$ is given as (38) with D_E denoting the distance between ground E to T$_i$.

In addition, we also investigate the air-to-ground channel, and g_i represents the channel power gain from the energy supplier drone to T$_i$ with LoS and NLoS connections given by [5]

$$\begin{aligned} g_i =& P_L \times (\sqrt{x^2+y^2+H_U^2})^{-\alpha_f} \\ &+ P_{NL} \times \delta(\sqrt{x^2+y^2+H_U^2})^{-\alpha_f}, \end{aligned} \tag{39}$$

where the position of T$_i$ is (x,y) in coordinates, $P_L = 1/(1 + m \times \exp(-n[\Phi - m]))$ represents the LoS probability, m and n are determined by the environment. Then, P_{NL}=1-P_L, δ is the excessive attenuation factor and α_f represents the pathloss of the air-to-ground channel. Furthermore, the elevation angle value $\Phi = 180/\pi \times \sin(H_U/\sqrt{(x^2+y^2+{H_U}^2)})^{-1}$. It is assumed that P_m=5W, α=3, α_g=3, β=-30 dB, η = 0.8, a=11.95 and b=0.136, γ=20dB and the QoS constraint is 10^{-2} bps/Hz. Similarly, the channel power gain of the flying E and T$_i$ can be obtained in (39) with H_E.

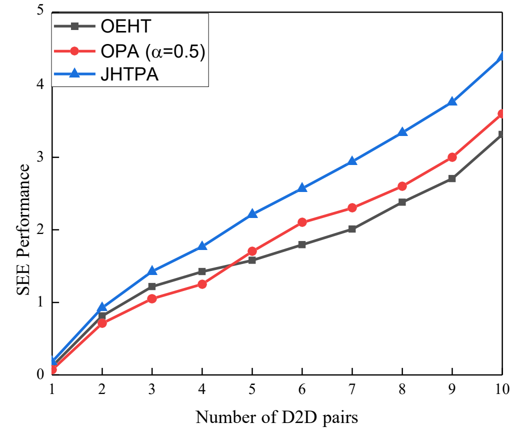

Fig. 2: The SEE of the three algorithms.

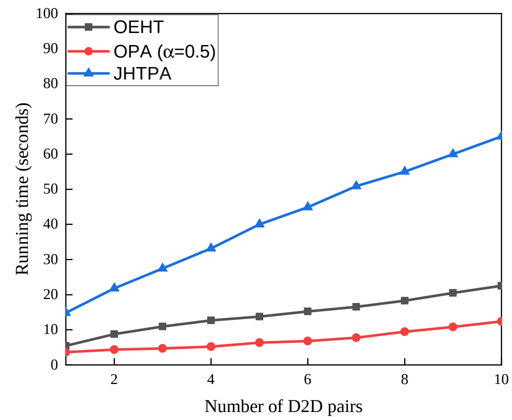

Fig. 3: The average computing time of the three proposed algorithms.

Fig. 2 shows the SEE performance of three algorithms with various number of D2D pairs. The JHTPA algorithm maximizes the SEE by jointly optimizing the α and $\mathbf{p}$ parameters. The OPA algorithm aims to optimize the power allocation with fixed energy harvesting time, we set it as α=0.5. In addition, the OEHT algorithm optimizes the energy harvesting time parameter while the power equals the maximum harvested power at each transmitter, as provided in (22). In Fig. 2, JHTPA has better SEE performance than OEHT and OPA across various D2D pairs. Interestingly, with the increase of the number of D2D pairs, OPA performs better than OEHT. This illustrates that when the number of D2D pairs is low, optimizing the energy harvesting parameter dominates the improvement of SEE performance, while when the number of D2D pairs is high, adaptive power allocation plays a major role in the improvement of SEE performance. Thus, OPA is a better optimization solution than OEHT when there is large

This article has been accepted for publication in IEEE Communications Letters. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/LCOMM.2023.3289881

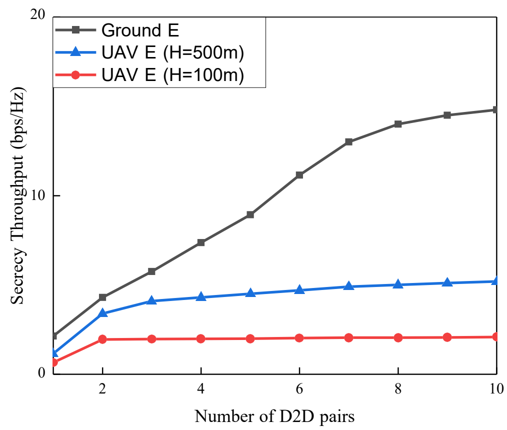

Fig. 4: Secrecy throughput under ground E and flying E with JHTPA algorithm.

number of D2D pairs.

We further present the running time of the optimization algorithms in Fig. 3. With the increase of D2D pairs, the convergence time of the three optimization algorithms grows. In addition, JHTPA needs longer convergence time than OPA and OEHT due to higher algorithm complexity. Although JHTPA takes the longest running time, it has the best SEE performance in comparison to the other two optimization algorithms as shown in Fig. 2. From Fig. 2 and Fig. 3, OPA outperforms OEHT when the number of D2D pairs increases, and the convergence time of OPA is shorter than OEHT. Therefore, OPA algorithm has better performance than OEHT. In addition, the proposed algorithms should be selected according to the requirements of the real wireless scenarios. For applications requiring a high level of SEE, JHTPA is a more desirable approach. Regarding the low-latency applications, OPA is a more suitable algorithm with low complexity and short convergence time.

Fig. 4 displays the secrecy throughput of the considered system with ground E and flying E, respectively. We consider three scenarios: 1) E is on the ground; 2) E is UAV with flying height of 100m, 3) E is UAV with flying height of 500m. We only apply JHTPA in this scheme since it has better SEE performance than the other two algorithms, as demonstrated in Fig. 2. In Fig. 4, the system has significantly higher secrecy throughput when E is on the ground. In particular, the differences of secrecy throughput between ground E and flying E are more obvious with an increase in the number of D2D transmitter pairs. Such pattern demonstrates that the NLoS connections between the transmitters and ground E lead to a worse eavesdropping channel condition, resulting in a high secrecy throughput of the system. Conversely, the channels between transmitters and flying E are LoS connections, which lead to a better wiretap channel condition. When the flying height of drone E declines, E has even better channel conditions, consequently, the secrecy throughput of the system drops. The simulation results highlight the impact of various channel conditions between eavesdropper and transmitter on the secrecy performance, and the LOS wiretap channel is shown to bring more threats to the system. Furthermore, this system is also shown to be sensitive to the movement of flying eavesdropper as the secrecy throughput decreases when flying E moves closer to the transmitter. This result proves that flying E is more harmful than ground E, especially when the distance between flying E and transmitter is short, which opens the system for further research in utilizing artificial noise and beamforming techniques in system design.

VI. Conclusion

We proposed resource allocation algorithms for wireless powered D2D communications assisted by UAV in the presence of ground and flying eavesdroppers. The results shows that the proposed algorithms are suitable for UAV applications and enhance the secrecy performance. For future works, we consider investigating trajectory optimization and optimal deployment UAV. This will involve a joint design of power allocation, trajectory and optimal deployment of UAV by using path-following algorithm. Our future work also aims to meet the low-latency requirement of the networks by applying cross-layer optimization and deep learning techniques [11].

References

[1] J. Lyu, H.-M. Wang, and K.-W. Huang, "Physical layer security in D2D underlay cellular networks with poisson cluster process," *IEEE Trans. Commun.*, vol. 68, no. 11, pp. 7123–7139, 2020.

[2] Y. Wu, G. Ji, T. Wang, L. Qian, B. Lin, and X. Shen, "Non-orthogonal multiple access assisted secure computation offloading via cooperative jamming," *IEEE Trans. Veh. Technol.*, vol. 71, no. 7, pp. 7751–7768, 2022.

[3] Z. Sheng, H. D. Tuan, A. A. Nasir, T. Q. Duong, and H. V. Poor, "Power allocation for energy efficiency and secrecy of wireless interference networks," *Trans. Wireless Commun.*, vol. 17, no. 6, pp. 3737–3751, 2018.

[4] G. Sun, J. Li, A. Wang, Q. Wu, Z. Sun, and Y. Liu, "Secure and energy-efficient UAV relay communications exploiting collaborative beamforming," *IEEE Trans. Commun.*, vol. 70, no. 8, pp. 5401–5416, 2022.

[5] M.-N. Nguyen, L. D. Nguyen, T. Q. Duong, and H. D. Tuan, "Real-time optimal resource allocation for embedded UAV communication systems," *IEEE Wireless Commun. Lett.*, vol. 8, no. 1, pp. 225–228, 2018.

[6] P. Chen, X. Zhou, J. Zhao, F. Shen, and S. Sun, "Energy-efficient resource allocation for secure D2D communications underlaying UAV-enabled networks," *Trans. Veh. Technol.*, 2022.

[7] Y. Xu, G. Gui, H. Gacanin, and F. Adachi, "A survey on resource allocation for 5G heterogeneous networks: Current research, future trends, and challenges," *IEEE Commun. Surv. Tut.*, vol. 23, no. 2, pp. 668–695, 2021.

[8] Y. Yin, M. Liu, G. Gui, H. Gacanin, H. Sari, and F. Adachi, "Cross-layer resource allocation for UAV-assisted wireless caching networks with NOMA," *IEEE Trans. Veh. Technol.*, vol. 70, no. 4, pp. 3428–3438, 2021.

[9] H. Wang, J. Wang, G. Ding, L. Wang, T. A. Tsiftsis, and P. K. Sharma, "Resource allocation for energy harvesting-powered D2D communication underlaying UAV-assisted networks," *IEEE Trans. Green Commun. Netw.*, vol. 2, no. 1, pp. 14–24, 2017.

[10] B. R. Marks and G. P. Wright, "A general inner approximation algorithm for nonconvex mathematical programs," *Operations research*, vol. 26, no. 4, pp. 681–683, 1978.

[11] A. Masaracchia, Y. Li, K. K. Nguyen, C. Yin, S. R. Khosravirad, D. B. Da Costa, and T. Q. Duong, "UAV-enabled ultra-reliable low-latency communications for 6G: A comprehensive survey," *IEEE Access*, vol. 9, pp. 137 338–137 352, 2021.