Energy Efficiency Optimization for D2D communications in UAV-assisted Networks with SWIPT

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Abstract—**This paper investigates the energy efficiency (EE) optimization problem for device-to-device (D2D) communications underlaying non-orthogonal multiple access (NOMA) unmanned aerial vehicles (UAVs)-assisted networks with simultaneous wireless information and power transfer (SWIPT). Our aim is to maximize the energy efficiency of the system while satisfying the constraints of transmission rate and transmission power budget. However, the considered EE optimization problem is non-convex involving joint optimization of the UAV's location, beam pattern, power control and time scheduling, which is difficult to solve directly. To tackle this problem, we develop an efficient resource allocation algorithm to decompose the original problem into several sub-problems and solve them sequentially. Specifically, we first apply the Dinkelbach method to transform the fraction problem to a subtractive-form one, and propose a mulitiobjective evolutionary algorithm based on decomposition (MOEA/D) based algorithm to optimize the beam pattern. We then optimize UAV's location and power control by applying the successive convex optimization techniques. Finally, after solving the above variables, the original problem is transformed into a single-variable problem with respect to the charging time, which is a linear problem and can be solved directly. Numerical results verify that the significant EE gain can be obtained by our proposed method as compared to the benchmark schemes.**

I. Introduction

Massive Machine-Type communications (mMTC) is an important scenario in the fifth generation (5G) mobile networks, this scenario is capable of supporting massive connections of Internet of Things (IoT) devices [1]. As a result, a massive number of connected IoT devices will cause the explosive growth of data traffic in IoT networks, resulting in enormous power consumption [2]. Thus, how to improve the energy efficiency (EE) of communication systems is still an open problem in the future wireless communication networks.

Simultaneous Wireless Information and Power Transfer (SWIPT) has been viewed as a promising technique for enhancing the energy efficiency of the systems [3], which achieves the information and energy to be simultaneously transmitted. In addition, Device-to-Device (D2D) is also one of the key technologies in the 5G mobile networks. It has been confirmed that combing SWIPT and D2D can further improve the energy efficiency [4].

However, when IoT devices are deployed in remote areas or disaster areas, it is not efficient for them to establish communication links with traditional base stations (BSs) due to long-distance transmission. Owning to their advantages of great maneuverability, wide coverage, and high flexibility, unmanned aerial vehicles (UAVs) have been widely deployed in geographically constrained areas to provide wireless services for users. Therefore, UAVs can act as air BSs to provide efficient information and energy transmission services for users, and thus have been widely used in many scenarios including non-orthogonal multiple access (NOMA) networks [5], multiple input multiple output (MIMO) systems [6], [7] and SWIPT networks [8].

In this paper, our aim is to maximize the EE of the UAV-assisted D2D communication network whilst satisfying the constraints of the minimum required data rate and transmit power. To tackle the design problem, we develop a multi-variable optimization algorithm, where all the variables are optimized in an alternative manner. First, we apply the Dinkelbach method to transform the fraction problem into a subtractive-form one. Then, we optimize the optimal UAV placement and transmit power in D2D phase by applying the successive convex optimization techniques. In addition, we adopt the multi-objective evolutionary algorithm based on decomposition (MOEA/D) [9] to control the beam pattern. Furthermore, we have proved that the corresponding sub-problem that optimizes the power allocation in SWIPT phase and time scheduling is convex which can be tackled by the standard convex optimization methods. Numerical results verify that significant computation performance gain can be achieved by the proposed algorithm compared with the benchmark schemes.

II. System Model and Problem Formulation

A. System Model

We consider a UAV-assisted D2D communication network with SWIPT. As seen in Fig. 1, the UAV is equipped with multiple antennas, and $K \geq 2$ D2D pairs is equipped with one single antenna due to the limitations of the hardware size and battery power. Each D2D transmitter (D2D-TX) $k \in \mathcal{K}$ has a fixed location on the ground which is denoted as $z_k^T = \left(x_k^T, y_k^T\right)$, and the kth D2D receiver (D2D-RX) is denoted as $z_k^R = \left(x_k^R, y_k^R\right)$. The horizontal location of UAV is denoted as $z_u = (x_u, y_u)$, and the UAV is assumed to work at a fixed altitude H. The whole period T_o contains two phases. In the SWIPT phase with duration $\tau_S T_o$ $(0 \leq \tau_S \leq 1)$, the

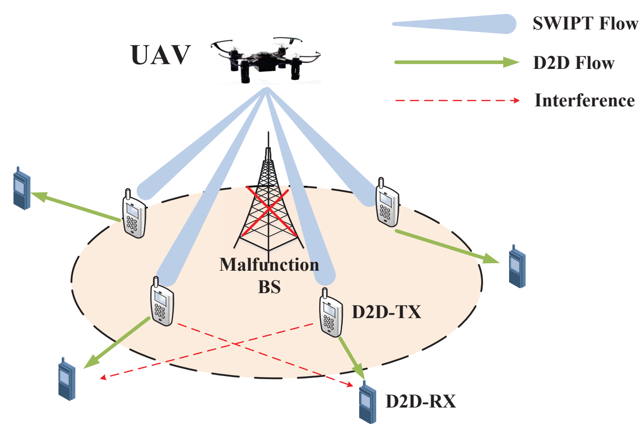

Fig. 1: Illustration of a UAV-assisted D2D communication network with SWIPT.

UAV transmits information and power to D2D-TXs. In the D2D phase with duration $\tau_D T_o$ ($\tau_D + \tau_S \leq 1$), the D2D-TXs transmit information to D2D-RXs using the harvested energy in the SWIPT phase. For simplicity, we set $T_o = 1$.

Sepcifically, in the SWIPT phase, UAV serves as a flying BS to transmit power and information to D2D-TX using NOMA. Since the UAV BS has the advantage of mobile flexibility, we assume that the communication links between the UAV and each D2D-TX is the line-of-sight (LOS) link. Thus, the channel gain between the UAV and the kth D2D-TX is expressed as [10]

$$\mathbf{h}_k = \sqrt{\rho_0 d_k^{-2}}\mathbf{a}(\theta, \phi), \tag{1}$$

where ρ_0 is the channel power gain at a reference distance of $d_0 = 1$ m. The distance between the UAV and kth D2D-TX is $d_k = \sqrt{\left(x_k^T - x_u\right)^2 + \left(y_k^T - y_u\right)^2 + H^2}$, and $\mathbf{a}(\theta, \phi)$ is the steering vector, which is given by

$$\mathbf{a}(\theta, \phi) = \Big[1, \cdots, e^{j2\pi/\lambda d \sin(\theta)[(j-1)\sin(\phi)+(i-1)\cos(\phi)]}, \\ \cdots, e^{j2\pi/\lambda d \sin(\theta)[(N-1)\sin(\phi)+(M-1)\cos(\phi)]}\Big]^T, \tag{2}$$

where θ is the elevation angle and ϕ is the azimuth angle of the LOS path. λ is the wavelength and d is the spacing between antenna elements. i and j is the coordinate of antenna elements. The channel power gain from the UAV to the kth D2D-TX is formulated as

$$\left|\mathbf{h}_k^H \mathbf{w}\right|^2 = \frac{\rho_0 \left|\mathbf{a}^H(\theta, \phi)\mathbf{w}\right|^2}{\left(x_k^T - x_u\right)^2 + \left(y_k^T - y_u\right)^2 + H^2}, \tag{3}$$

where $\mathbf{w}$ denotes the beamforming vector. $\mathbf{E}(\theta, \phi) = \mathbf{a}^H(\theta, \phi)\mathbf{w}$ represents the synthesized pattern of the antenna array, let $g_k^S = \left|\mathbf{h}_k^H \mathbf{w}\right|^2$. Each D2D-TX consists of the information decoding (ID) circuit and the energy harvesting (EH) rectification circuit. Power splitting (PS) scheme is adopted to split the signal into two parts, one of which is exploited for energy harvesting whilst the other part is used to decode the information. The power budget of UAV is limited to P_{max}, and the power allocated to the kth D2D-TX is assumed to be P_k^S. α_k^S denotes the fraction of transmission power allocated to kth D2D-TX for ID, and $1 - \alpha_k^S$ for EH. Thus, the signal received by kth D2D-TX for ID is expressed as

$$y_k^{ID} = \sqrt{\alpha_k^S} h_k \sum_{i=1}^{K} \sqrt{P_i^S} s_i + N_0, \tag{4}$$

where s_k denotes the signal from UAV to the kth D2D-TX, and N_0 is the additive Gaussian white noise (AWGN) with power σ^2. With successive interference cancellation (SIC) operation, the kth D2D-TX will detect the jth D2D-TX's information, $j < k$, and remove the information from its observation. The message for jth D2D-TX, $j > k$, will be treated as noise at the kth D2D-TX. Thus, the achievable transmission rate for D2D-TX k is given by

$$R_k^S = \log_2\left(1 + \frac{\alpha_k^S g_k^S P_k^S}{\sigma^2 + \alpha_k^S g_k^S \sum_{i=k+1}^{K} P_i^S}\right). \tag{5}$$

The signal received by kth D2D-TX for EH is expressed as

$$y_k^{EH} = \sqrt{1 - \alpha_k^S} h_k \sum_{i=1}^{K} \sqrt{P_i^S} s_i + N_0, \tag{6}$$

Then, the harvested energy at the kth D2D-TX is expressed as

$$E_k^S = \tau_S \left(1 - \alpha_k^S\right) \eta g_k^S \sum_{i=1}^{K} P_i^S, \tag{7}$$

where η represents the energy conversion efficiency. The total energy consumption of the SWIPT phase is expressed as

$$E_{\text{total}}^S = \tau_S \left(\zeta \sum_{k=1}^{K} P_k^S + P_C^S + P_{hov}\right) - \sum_{k=1}^{K} E_k^S, \tag{8}$$

where ζ denotes the drain efficiency of the power amplifier, P_C^S is the energy consumed by the hardware of the SWIPT phase, and P_{hov} denotes the power consumed of the UAV during hovering.

In the D2D phase, we assume that the communication links between the D2D-TX and D2D-RX is the LOS links due to the advantage of D2D links. Thus, the channel power gain from the mth D2D-TX to the kth D2D-RX is expressed as

$$g_{m,k}^D = \frac{\rho_0}{\left(X_m^T - x_k^R\right)^2 + \left(y_m^T - y_k^R\right)^2}. \tag{9}$$

The transmit power of the kth D2D-TX is assumed to be P_k^D. Thus, the achievable transmission rate of the kth D2D-RX is given by

$$R_k^D = \log_2\left(1 + \frac{g_{k,k}^D P_k^D}{\sigma^2 + \sum_{i=1, i\neq k}^{k} g_{i,k}^D P_i^D}\right). \tag{10}$$

In addition, the total energy consumption of the D2D phase can be expressed as

$$E_{total}^D = \sum_{k=1}^{K} E_k^D = \tau_D (\sum_{k=1}^{K} P_k^D + P_C^D), \tag{11}$$

where P_C^D denotes the energy consumed by the D2D phase. Therefore, the EE of the considered network can be formulated as

$$\lambda_{EE} = \frac{\tau_D \sum_{k=1}^{K} R_k^D}{E_{\text{total}}^S + E_{\text{total}}^D}. \tag{12}$$

B. Problem Formulation

We aim to maximize the energy efficiency of the network whilst satisfying the constraints of minimum transmit rate and total transmit power of UAV. Mathematically, the optimization problem can be expressed as

$$\max_{E(\theta,\phi),P_k^{S,D},z_u,\alpha_k^S,\tau_{S,D}} \quad \lambda_{EE} \tag{13a}$$

$$\text{s.t.} \quad R_k^S \geq R_{\min}^S, \forall k \in \mathcal{K}, \tag{13b}$$

$$R_k^D \geq R_{\min}^D, \forall k \in \mathcal{K}, \tag{13c}$$

$$\sum_{k=1}^{K} P_k^S \leq P_{\max}, \tag{13d}$$

$$E_k^D \leq E_k^S, \forall k \in \mathcal{K}, \tag{13e}$$

$$\tau_S + \tau_D \leq 1, \tag{13f}$$

$$0 \leq \tau_S, \tau_D \leq 1. \tag{13g}$$

$$0 \leq \alpha_k^S \leq 1. \tag{13h}$$

Constraints (13b), (13c) indicate the achievable rate in the SWIPT phase and the D2D phase should satisfy the minimum transmission rate constraints R_{min}^S and R_{min}^D respectively to guarantee the quality of service (QoS) of the devices. Constraints (13d) indicates that the transmission power of UAV should satisfy the maximize power budget P_{max}. Constraint (13e) guarantees that the energy consumed by each D2D-TX cannot exceed its harvested energy from the UAV. Constraints (13f) and (13g) limit time switching ratio for SWIPT phase and D2D phase, and constraint (13h) limits power splitting ratio for ID and EH. Problem (13) is a non-convex problem due to the coupling variables, which is challenging to solve. To tackle this problem, we develop an efficient resource allocation algorithm by optimizing the above variables sequentially.

III. THE ITERATIVE RESOURCE ALLOCATION ALGORITHM

In this section, we develop an iterative joint UAV location and resource allocation algorithm where the designed problem is decoupled into several problems and solved then sequentially. Specifically, since the beam pattern design requires the beam scanning angles, the UAV location should be determined first. Then, based on the acquisition of angle information, the beam pattern is obtained. Subsequently, with the fixed UAV's placement and beam pattern design, the PS ratio and power allocation in SWIPT phase are optimized. Finally, the power allocation in D2D phase is optimized to maximize the EE of the system.

We first apply the Dinkelbach method [11] to transform the fraction problem to a subtractive-form one. Denote q^* as the optimal solution of the considered problem (13), which is expressed as

$$q^* = \max_{E(\theta,\phi),P_k^{S,D},z_u,\alpha_k^S,\tau_{S,D}} \frac{\tau_D \sum_{k=1}^{K} R_k^D}{E_{\text{total}}^S + E_{\text{total}}^D}. \tag{14}$$

With the given q, the equivalent optimization problem can be given by

$$\begin{aligned} &\max_{E(\theta,\phi),P_k^{S,D},z_u,\alpha_k^S,\tau_{S,D}} \quad \lambda_{EE}^{'} \\ &= \sum_{k=1}^{K} \tau_D \left(\tilde{R}_k^D - \hat{R}_k^{Dub} \right) - q \left(E_{\text{total}}^S + E_{\text{total}}^D \right). \end{aligned} \tag{15}$$

A. Location Optimization

With the fixed beam pattern, power allocation, PS ratio and time scheduling factor, the original problem can be regarded as the UAV location optimization problem. This problem can be reformulated as:

$$\max_{z_u} \ \lambda_{EE}^{'} \tag{16a}$$

$$\text{s.t.} \ \log_2 \left(1 + \frac{\alpha_k^S g_k^S P_k^S}{\sigma^2 + \alpha_k^S g_k^S \sum_{i=k+1}^{K} P_i^S} \right) \geq R_{min}^S, \forall k \in \mathcal{K}, \tag{16b}$$

$$\tau_S \left(1 - \alpha_k^S \right) \eta g_k^S \sum_{i=1}^{K} P_i^S \geq E_k^D, \forall k \in \mathcal{K}. \tag{16c}$$

The constraints (16b) are non-convex with respect to z_u. By applying the successive convex optimization approach, R_k^S is reformulated as

$$R_k^S = \tilde{R}_k^S - \hat{R}_k^S, \tag{17}$$

where

$$\tilde{R}_k^S = \log_2 \left(\frac{\rho_0 \alpha_k^S |E(\theta,\phi)|^2}{H^2 + \left\| z_k^T - z_u \right\|^2} \sum_{k=1}^{K} P_i^S + \sigma^2 \right), \tag{18}$$

$$\hat{R}_k^S = \log_2 \left(\frac{\rho_0 \alpha_k^S |E(\theta,\phi)|^2}{H^2 + \left\| z_k^T - z_u \right\|^2} \sum_{k=i+1}^{K} P_i^S + \sigma^2 \right). \tag{19}$$

Noted that $\tilde{R}_k^S$ is neither concave nor convex with respect to z_u.

We define the local point z_u^r as the given location of UAV in the rth iteration. Then, we obtain the globally lower bound of (18) by applying the first order Taylor expansion [12], which is expressed as

$$\begin{aligned} \tilde{R}_k^S &= \log_2 \left(\frac{\rho_0 \alpha_k^S |E(\theta,\phi)|^2}{H^2 + \left\| z_k^T - zu \right\|^2} \sum_{k=1}^{K} P_i^S + \sigma^2 \right) \\ &\geq \sum_{i=1}^{k} -A_k^r (\left\| z_k^T - z_u \right\|^2 - \left\| z_k^T - z_u^r \right\|^2) \\ &\quad + B_k^r \triangleq \tilde{R}_k^{Slb}, \end{aligned} \tag{20}$$

where A_k^r and B_k^r can be calculated as

$$A_k^r = \frac{\frac{P_i^S \rho_0 \alpha_k^S |E(\theta,\phi)|^2}{\left(H^2 + \left\| \mathbf{z}_k^T - \mathbf{z}_u^r \right\|^2 \right)^2} \log 2(e)}{\frac{\rho_0 \alpha_k^S |E(\theta,\phi)|^2}{H^2 + \left\| \mathbf{z}_k^T - \mathbf{z}_u^r \right\|^2} \sum_{l=1}^{k} P_l^S + \sigma^2}, \tag{21}$$

$$B_k^r = \log_2\left(\frac{\rho_0\alpha_k^S|E(\theta,\phi)|^2}{H^2+\left\|\mathbf{z}_k^T-\mathbf{z}_u^r\right\|^2}\sum_{l=1}^{k}P_l^S+\sigma^2\right). \tag{22}$$

With (17) and (20), (16b) can be reformulated as

$$\tilde{R}_k^{Slb} - \hat{R}_k^S \geq R_{min}^S. \tag{23}$$

However, (23) is still non-convex due to $\hat{R}_k^S$. Thus, we introduce slack variable $\mathbf{S}=\left\{S_k=\left\|\mathbf{z}_k^T-\mathbf{z}_u\right\|^2,\forall k\right\}$, which should satisfy the following conditions

$$S_k \leq \left\|\mathbf{z}_k^T-\mathbf{z}_u\right\|^2, \forall k \tag{24}$$

Then, $\hat{R}_k^S$ can be reformulated as

$$\hat{R}_k^S = \log_2\left(\frac{\rho_0\alpha_k^S|E(\theta,\phi)|^2}{H^2+S_k}\sum_{k=i+1}^{K}P_i^S+\sigma^2\right). \tag{25}$$

Since $\left\|\mathbf{z}_k^T-\mathbf{z}_u\right\|^2$ is convex with respect to z_u, we have the following inequality via Taylor expansion at the given point z_u^r

$$\left\|z_k^T-z_u\right\|^2 \geq \left\|Z_k^T-z_u^r\right\|^2+2\left(z_k^T-z_u^r\right)^{\mathbf{T}}\left(z_u-z_u^r\right). \tag{26}$$

By substituting (26), problem (16) is approximated as the following problem

$$\max_{z_u,S}\ \lambda_{EE} \tag{27a}$$

$$\text{s.t.}\ \ \tilde{R}_k^{Slb}-\log_2\left(\frac{\rho_0\alpha_k^S|E(\theta,\phi)|^2}{H^2+S_k}\sum_{k=i+1}^{K}P_i^S+\sigma^2\right) \tag{27b}$$

$$\geq R_{min}^S, \forall k\in\mathcal{K},$$

$$\tau_S\left(1-\alpha_k^S\right)\eta g_k^S\sum_{i=1}^{K}P_i^S \geq E_k^D, \forall k\in\mathcal{K}, \tag{27c}$$

$$S_k \leq \left\|Z_k^T-z_u^r\right\|^2+2\left(z_k^T-z_u^r\right)^{\mathbf{T}}\left(z_u-z_u^r\right). \tag{27d}$$

As a result, problem (27) is convex now, and can be efficiently tackled by the standard convex optimization methods.

B. Optimal Phased-Array Pattern

With the fixed UAV location, power allocation, PS ratio and time scheduling, the optimization problem with respect to the beam pattern can be expressed as:

$$\max_{E(\theta,\phi)}\ \lambda_{EE}^{'} \tag{28a}$$

$$s.t.\ \ R_k^S \geq R_{\min}^S, \forall k\in\mathcal{K}, \tag{28b}$$

$$E_k^D \leq E_k^S, \forall k\in\mathcal{K}. \tag{28c}$$

From (3) and (12), the channel power gain g_k^S increases with $E(\theta,\phi)$. As a result, the channel power gain increases, results in a significantly enhancement of the EE and achievable transmission rate. Hence, problem (28) can be rewritten as

$$\max\ \ |\mathbf{E}(\theta,\phi)|^2. \tag{29}$$

The $M\times N$ antenna array can be divided into several sub-arrays, we assumed that the steerable beams formed by the sub-arrays are independent. Then, problem (29) can be reformulated as

$$\max\ \ E_k(\theta,\phi). \tag{30}$$

To form the directional beams, we control the side-lobe level (SLL), array gain and beamwidth simultaneously through optimizing the phase of antenna element. Mathematically, the beam pattern multiobjective optimization problem (MOP) with respect to phase $\boldsymbol{z}$ can be constructed as

$$\begin{aligned}&\min F(\boldsymbol{z})=(f_1(\boldsymbol{z}),f_2(\boldsymbol{z}),f_3(\boldsymbol{z}))^{\mathbf{T}}\\&\text{s.t. } \boldsymbol{z}\in\mathbf{R}^{M\times N},\end{aligned} \tag{31}$$

where $f_1(\boldsymbol{z})=SLL(\boldsymbol{z}), f_2(\boldsymbol{z})=\frac{1}{|\mathbf{E}(\theta,\phi)|}, f_3(\boldsymbol{z})=\frac{1}{\Theta_{h,e}}$, $\boldsymbol{z}=[z_{1n},\cdots,z_{mn},\cdots,z_{MN}]^{\mathbf{T}}$ denotes the phases of the $M\times N$ antenna array. $SLL(\boldsymbol{z})=20\log\frac{|\mathrm{F}_{sll}|}{|\mathrm{F}_{ml}|}$ denotes the side-lobe level of the antenna array, where F_{sll} and F_{ml} represent the array factor of the maximum SLL and main lobe [13], respectively. $\mathbf{E}(\theta,\phi)=\mathbf{a}^H(\theta,\phi)e^{j\boldsymbol{z}}$ represents the synthesized pattern and $\Theta_{h,e}$ denotes the elevation plane half-power beamwidth. To tackle problem (31), we apply the MOEA/D solution [9]. Here, the steps of the algorithm can be described as follows:

- *Input*: Let $\{N_0,\gamma^i,S\}$ be a set of input parameters. Here, N_0 is the number of subproblems. $\gamma^i=(\gamma_1^i,...,\gamma_d^i)^T$, $i=1,...,N_0$, d represents the weight vector of the ith subproblem. S denotes the number of weight vectors in each neighborhood.
- *Output*: EP: a non-dominated solutions set.
- *Initialization*: For each $i=1,...,N_0$, we select S as the closest weight vectors of γ^i by calculating the Euclidean distance, and store them in $C(i)$. Then, we produce the initial solutions $z_1,...z_{N_0}$ randomly, and update the F-values $FV_i=F(z_i)$. In addition, we initiate the best-so-far solutions $\beta=(\beta_1,...,\beta_j,...,\beta_{N_d})^T$, where $\beta_j=min\{f_j(z),z\in\mathbf{R}^{M\times N}\}$, and set EP to be empty.
- *Update*: For each $i=1,...,N_0$, we choose weight vectors z_k, z_l from $C(i)$, and generate the new solution x. Then, for $j=1,...,d$, if $\beta_j>f_j(x)$, it follows that $\beta_j=f_j(x)$; If $g^{te}\left(x\mid\gamma^j,\beta\right)\leq g^{te}\left(z_j\mid\gamma^j,\beta\right)$, it follows that $z_j=x$ and $FV_j=F(x)$, where $g^{te}\left(x\mid\gamma^j,\beta\right)=\max_{1\leq t\leq d}\{\gamma_t^j\left|f_t(\boldsymbol{x})-\beta_t\right|\}$ [9]. Then, we remove all vector dominated by $F(x)$ from EP, if no vectors dominate $F(x)$, we add it to EP.
- *Stopping*: The iterations have converged.

C. Optimal PS Ratio and Power Allocation in SWIPT Phase

We optimize the PS ratio and power allocation in SWIPT phase respectively with the fixed UAV location, beam pattern, power allocation in D2D phase and time scheduling. The optimization problem is expressed as:

$$\max_{P_k^S,\alpha k^S}\ \lambda_{EE}^{'} \tag{32a}$$

$$\text{s.t.}\ \ R_k^S \geq R_{\min}^S, \forall k\in\mathcal{K}, \tag{32b}$$

$$\sum_{k=1}^{K}P_k^S \leq P_{\max}, \tag{32c}$$

$$\tau_S\left(1-\alpha_k^S\right)\eta g_k^S\sum_{i=1}^{K}P_i^S \geq E_k^D, \forall k\in\mathcal{K}. \tag{32d}$$

The objective function is strictly concave with respect to P_k^S and $\alpha_k^S, \forall k\in\mathcal{K}$. Note that the constraint (32b) can be rewritten as

$$\sigma^2+\alpha_k^S g_k^S \sum_{i=k}^{K} P_i^S - 2^{R_{min}^S}\left(\sigma^2+\alpha_k^S g_k^S \sum_{i=k+1}^{K} P_i^S\right) \geq 0. \tag{33}$$

Constraint (33) is claerly linear. Thus, the optimization problem (32) is convex with respect to P^S and α^S, and can be tackled by the standard convex optimization methods.

D. Power Allocation in D2D Phase

With the fixed UAV location, beam pattern, power allocation in SWIPT phase and time scheduling, we discuss the power allocation in D2D phase. The resulting optimization problem is expressed as

$$\max_{P_k^D} \ \lambda_{EE}^{'} \tag{34a}$$

$$\text{s.t.} \ \ R_k^D \geq R_{\min}^D, \forall k \in \mathcal{K}, \tag{34b}$$

$$\tau_D\left(\sum_{k=1}^{K} P_k^D + P_C^D\right) \leq E_k^S, \forall k \in \mathcal{K}. \tag{34c}$$

Problem (34) is challenging to solve due to the non-convex function (34a) and constraint (34b). To tackle this problem, we apply the successive convex optimization technique. In particular, we first rewrite R_k^D as

$$R_k^D = \tilde{R}_k^D - \hat{R}_k^D, \tag{35}$$

where

$$\tilde{R}_k^D = \log_2\left(\sum_{i=1}^{K} g_{i,k}^D P_i^D + \sigma^2\right), \tag{36}$$

and

$$\hat{R}_k^D = \log_2\left(\sum_{i \neq k}^{K} g_{i,k}^D P_i^D + \sigma^2\right). \tag{37}$$

Let P^{Dr} be the rth iteration of P^D. By applying the Taylor expansion, the upper bound of (37) is rewritten as

$$\begin{aligned}\hat{R}_k^D &= \log_2\left(\sum_{i \neq k}^{K} g_{i,k}^D P_i^D + \sigma^2\right)\\ &\leq \sum_{i \neq k}^{K} C_{i,k}^r (P_i^D - P_i^{Dr}) + \log_2\left(\sum_{i \neq k}^{K} g_{i,k}^D P_i^{Dr} + \sigma^2\right)\\ &\triangleq \hat{R}_k^{Dub},\end{aligned} \tag{38}$$

where

$$C_{i,k}^r = \frac{g_{i,k}^D \log_2(e)}{\sum_{l \neq k}^{K} g_{l,k}^D P_l^{Dr} + \sigma^2}. \tag{39}$$

TABLE I
THE RESOURCE ALLOCATION ALGORITHM

1: Initialize $\mathbf{Z}^n, \mathbf{E}^n, \mathbf{P_S}^n, \mathbf{A_S}^n, \mathbf{P_D}^n, \mathbf{T}^n$. Calculate $\mathbf{Q}^n = \lambda_{EE}^n$, and set iterate index n=1; 2: **ITERATE** For given $\mathbf{Q}^n, \mathbf{E}^n, \mathbf{P_S}^n, \mathbf{A_S}^n, \mathbf{P_D}^n, \mathbf{T}^n$, solve problem (27) and obtain optimal $\mathbf{Z}^{n+1}$. For given $\mathbf{Q}^n, \mathbf{Z}^{n+1}, \mathbf{P_S}^n, \mathbf{A_S}^n, \mathbf{P_D}^n, \mathbf{T}^n$, solve problem (32) and obtain optimal $\mathbf{E}^{n+1}$. For given $\mathbf{Q}^n, \mathbf{Z}^{n+1}, \mathbf{E}^{n+1}, \mathbf{A_S}^n, \mathbf{P_D}^n, \mathbf{T}^n$, solve problem (33) and obtain optimal $\mathbf{P_S}^{n+1}$. For given $\mathbf{Q}^n, \mathbf{Z}^{n+1}, \mathbf{E}^{n+1}, \mathbf{P_S}^{n+1}, \mathbf{P_D}^n, \mathbf{T}^n$, solve problem (35) and obtain optimal $\mathbf{A_S}^{n+1}$. For given $\mathbf{Q}^n, \mathbf{Z}^{n+1}, \mathbf{E}^{n+1}, \mathbf{P_S}^{n+1}, \mathbf{A_S}^{n+1}, \mathbf{T}^n$, solve problem (43) and obtain optimal $\mathbf{P_D}^{n+1}$. For given $\mathbf{Q}^n, \mathbf{Z}^{n+1}, \mathbf{E}^{n+1}, \mathbf{P_S}^{n+1}, \mathbf{A_S}^{n+1}, \mathbf{P_D}^{n+1}$, solve problem (44) and obtain optimal $\mathbf{T}^{n+1}$. Calculate $\mathbf{Q}^{n+1} = \lambda_{EE}^{n+1}$, Update n = n + 1. 3: **UNTIL** converge.

By substituting (38) into problem (34), problem (34) can be represented as

$$\max_{P_k^D} \ \sum_{k=1}^{K} \tau_D\left(\tilde{R}_k^D - \hat{R}_k^{Dub}\right) - q\left(E_{\text{total}}^S + E_{\text{total}}^D\right) \tag{40a}$$

$$\text{s.t.} \ \ \log_2\left(\sum_{i=1}^{K} g_{i,k}^D P_i^D + \sigma^2\right) - \hat{R}_k^{Dub} \geq R_{min}^D, \tag{40b}$$

$$\tau_D\left(\sum_{k=1}^{K} P_k^D + P_C^D\right) \leq E_k^S, \forall k \in \mathcal{K}. \tag{40c}$$

Thus, problem (40) is convex now, and can be tackled by the standard convex optimization methods.

E. Time Scheduling

With the fixed UAV location, power allocation, beam pattern and PS ratio, problmen (13) is simplified as

$$\max_{\tau_S,\tau_D} \ a_0\tau_S + a_1\tau_D \tag{41a}$$

$$\text{s.t.} \ \ a_2\tau_S \leq a_3\tau_D, \tag{41b}$$

$$\tau_S + \tau_D \leq 1, \tag{41c}$$

$$0 \leq \tau_S, \tau_D \leq 1. \tag{41d}$$

where $a_0 = -q(P_{hov} + P_C^S - \sum_{k=1}^K \eta\left(1-\alpha_k^S\right) g_k^S \sum_{i=1}^K P_i^s + \xi \sum_{k=1}^K P_k^S), a_1 = -q\left(\sum_{k=1}^K P_k^D + P_C^D\right) + \sum_{k=1}^K R_k^D, a_2 = \sum_{k=1}^K P_k^D + P_C^D, a_3 = \left(1-\alpha_k^S\right)\eta g_k \sum_{i=1}^K P_i^S$. Since the problem is a linear programming problem, it can be solved directly.

Based on the previous subsections, the complete iterative algorithm for problem (13) is summarized in TABLE I. To simplify the description, let $\mathbf{Z} = \{z_u\}$, $\mathbf{E} = \{E(\theta,\phi)\}$, $\mathbf{P_S} = \{P_k^S, \forall k\}$, $\mathbf{A_S} = \{\alpha_k^S, \forall k\}$, $\mathbf{P_D} = \{P_k^D, \forall k\}$, $\mathbf{T} = \{\tau_S, \tau_D\}$.

IV. NUMERICAL RESULTS

In this section, we provide the numerical results to demonstrate the superiority of our proposed algorithm. It is assumed

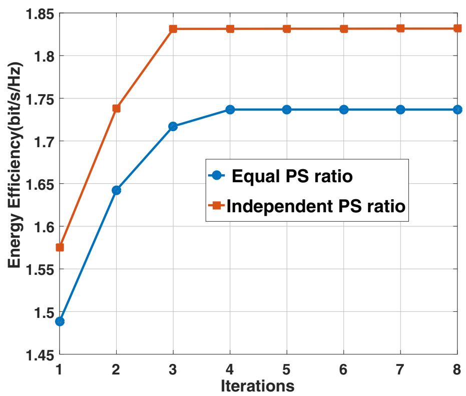

Fig. 2: Convergence performance of the proposed algorithm with different PS ratio scheme.

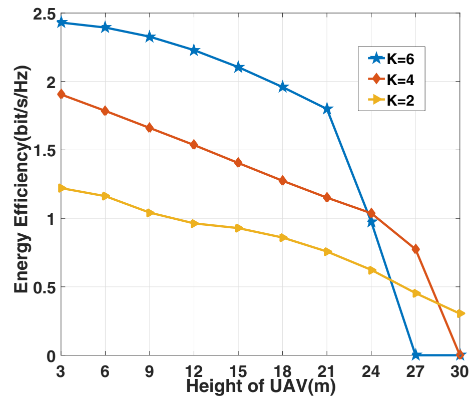

Fig. 4: The performance of the proposed algorithm with different height of UAV and number of D2D pairs.

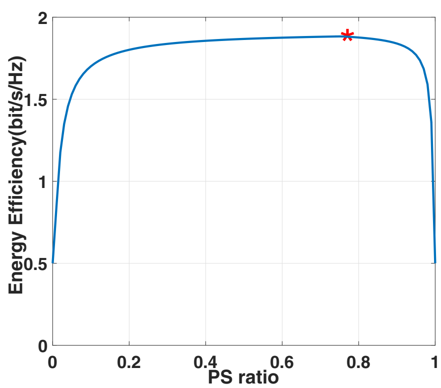

Fig. 3: The performance of the proposed algorithm versus equal PS ratio.

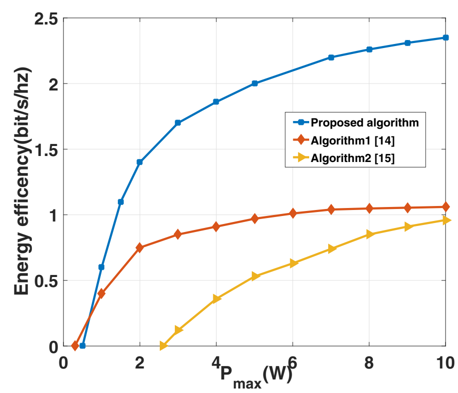

Fig. 5: Impact of the maximum transmit power on the EE performance under different algorithm.

that the UAV-assisted D2D communication network has $K = 4$ D2D pairs. Other parameters are as follows: $\sigma^2 = -110$ dBm, $\rho_0 = -40$ dB, $H = 20$ m, $P_{hov} = 110$ W, $P_C^S = 5$ mW, $P_C^D = 10$ μW, $\eta = 0.6$, $\zeta = 0.1$, $R_{min}^S = 2$ bit/s/Hz, $R_{min}^D = 1$ bit/s/Hz, $P_{\max} = 5$ W.

In the first simulation, we study the convergence of our proposed algorithm with different PS ratio strategy. As seen in Fig. 2, the EE of the both two cases converge to a fixed value within three iterations. In addition, the independent PS ratio case can achieve higher EE, but cost higher computational complexity.

In the next simulation, the relationship between the EE and the PS ratio is studied. This case involves $K = 4$ D2D pairs with equal PS ratio scheme. As shown in Fig. 3, the relationship between the EE and the PS ratio is quasiconcave. This demonstrates that there is a trade-off between the PS scheme for EH and ID. In particular, a high PS ratio reduces the energy harvested by D2D-TXs, which in turn reduces the throughput in D2D phase. In contrast, a low PS ratio may increase the energy harvested by D2D-TXs. However, in order to satisfy the minimum transmission rate constraints in the SWIPT phase, the UAV has to use a larger transmission power, resulting in a decrease in the EE performance. In other words, a suitable value of PS ratio can increase the overall EE performance.

Furthermore, the EE of the D2D communications underlaying UAV-assisted IoT system versus the height of UAV is evaluated under different number of D2D pairs. In particular, we set the number of D2D pairs to 2, 4 and 6 respectively, and set the height of UAV within the range of 3 m to 30 m. As it can be shown in Fig. 4, the EE achieved by our proposed algorithm decreases monotonically with the height of UAV. Furthermore, in the case of $K = 6$ D2D pairs, the EE decreases rapidly when the height of UAV reaches at 21 m. This is due to the fact that increasing the UAV's height will increase the path loss, and hence restricts the improvement of the EE performance. In addition, the EE is non-decreasing with the number of D2D pairs. This is due to the fact that a larger number of D2D pairs is capable of enhancing the diversity gain. Therefore, a suitable number of D2D pairs can achieve a better EE performance.

In the last simulation, we study the relationship between the EE and P_{max}. To show the computation performance, we compare with algorithm 1 in [14] and algorithm 2 in [15]. In

Fig. 5, the EE achieved by our proposed algorithm outperforms both algorithm 1 and algorithm 2. This is because algorithm 1 use a single antenna which causes the poor channel conditions. In algorithm 2, the sum throughput becomes lower without considering D2D. Furthermore, our algorithm adopts NOMA which further increases the EE of the network.

V. Conclusion

In this paper, we study the energy efficiency problem for a D2D communications underlaying NOMA in UAV-assisted network, where a UAV serves as a flying BS to transmit energy and information to D2D-TXs, and D2D-TXs transmit information to D2D-RXs by the harvested energy. We aim to maximize the EE of the network while satisfying the constraints of minimum transmit rate and maximum transmit power. The EE maximization problem involves joint optimization of the UAV location, beam pattern design, power allocation and time scheduling, which is non-convex and challenging to solve. To tackle this problem, by applying the Dinkelbach method, the successive convex optimization techniques and the MOEA/D algorithm, we propose a iterative resource allocation algorithm to optimize the variables sequentially. Numerical results illustrate the EE achieved by our proposed iterative algorithm outperform two existing works.

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