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D2D Communications Underlaying UAV-Assisted Access Networks

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ABSTRACT Unmanned aerial vehicles (UAVs)-enabled base stations (BSs) can boost the system performance of the terrestrial networks with device-to-device (D2D) communication in the scenarios that fixed BSs in the ground are not available. However, the serious interference among UAVs and multiple D2D pairs is more challenging than the terrestrial case because UAVs are changing the networks topology frequently over time. In this paper, the power control optimization is investigated for D2D communications underlaying UAV-assisted access systems, where a UAV-enabled BS serves multiple users, and the remaining users communicate with each other with the assistance of the UAV, also referred to as D2D pairs. With the aim of throughput maximization, we need to address a non-convex optimization. To this end, difference of two convex functions (D.C.) programming is invoked to solve the formulated optimization, which can obtain suboptimal solutions. Considering the UAV's limited energy and low computational capability, we further design a low-complexity power control algorithm by exploiting the Hessian matrix's structure. Simulation results show that the proposed algorithms perform quite well for all considered scenarios. Both of them can improve the system throughput dramatically. Moreover, the low-complexity algorithm produces almost the same throughput as the D.C. programming method with much lower computation burden.

INDEX TERMS Device-to-device (D2D) communications, D.C. programming, power control, unmanned aerial vehicle (UAV).

I. INTRODUCTION

Unmanned aerial vehicle (UAV)-assisted communications have caught increasing interests recently due to its high mobility [2]–[4]. UAVs can serve as aerial base stations (BSs) to enhance the wireless coverage and boost throughput at hotspots such as campuses and sport stadiums, or in the cases without infrastructure for wireless access, such as the regions where the cellular infrastructure has been damaged due to natural disasters [5], [6]. As mobile relays, they can rapidly provide wireless connectivity for a group of separated users with unreliable communication links [7], [8]. Compared to traditional static relays, UAV-enabled mobile relays can be deployed much more swiftly and improve the system throughput performance by dynamically adjusting relay locations. Besides, in most scenarios, it can build an almost line of sight (LOS) transmission link, which potentially improves the system performance [8]. Wang *et al.* [3] have shown its potentials in ultra dense networks from the perspective of communications, caching and energy transfer. However, its high agility also brings many technical challenges, such as path planning and imperfect channel state. In this context, the air-to-ground channel [9]–[11] and network performance [12]–[18] recently have been researched.

In UAV-assisted communications, the classical fading channel model is not applicable to the air-to-ground (ATG) communication link between the aerial UAV and its served users. Prior works have shown that the ATG link can be characterized by LOS and non-LOS links with their occurrence probabilities [9]–[11]. These researches lay the groundwork to further study the UAV-involved communications [12]–[18]. Specifically, the optimal altitudes of one or two low altitude aerial platforms are studied to maximize the radio coverage in [12] and minimize the required transmit power in [13], respectively. Mozaffari *et al.* [15] extend it to the multiple UAVs case with the aim to minimize the energy consumption. A user demand based UAV deployment method for heterogenous networks is developed in [16], where UAVs are harnessed to realize a reliable and load balanced network. Additionally, the coverage and rate performance are discussed in detail in [17] and [18]. In [17], a coexistence network for a UAV and multiple device-to-device (D2D) pairs is considered, where an analytical framework for the throughput and coverage is derived. Zhang and Zhang [18] study a 3D scenario that users are modeled by Poisson point process. The above mentioned studies mainly focus on analyzing or improving the system performance from the perspective of UAV deployment [12]–[18]. Few of existing studies perform system optimization from the point of view of power control [19].

Meanwhile, D2D communication is another effective approach to improve coverage and capacity for the regions where no infrastructure can be used [20]–[22]. However, the coexistence of UAVs and D2D communications generates serous interference, which inevitably degrades the system performance. Thus, interference management is of paramount importance for UAV-assisted access networks with D2D communications, which, however, has not been well studied in the literature. The research on D2D communications underlaying cellular networks in conventional terrestrial case provides a guidance to address the interference between the UAV and D2D pairs [23]–[28]. Some early works related to the interference management for D2D communications focus on a classical case that contains a cellular user and one D2D pair [23], [24], which potentially limits the spectrum efficiency gains. More general scenarios containing multiple D2D pairs are investigated in [25]–[28]. In this context, one of challenging problems is the power control considering their mutual interference. The existing solutions to this problem can be classified into the two groups. One is to find a near/sub optimal solution by successive convex approximation, i.e., addressing a series of convex optimization problems. It can be addressed by standard convex optimization techniques such as interior point method (IPM) (see, e.g., [25] and [26]), however, with quite high complexity. From the perspective of game theory, designing distributed power control algorithms is another widely used approach (see, e.g., [27] and [28]). Nevertheless, the system performance at an equilibrium point achieved by game theory generally cannot guarantee the optimality. Considering the UAV's characteristics, such as the limited energy and low computational capability, a low-complexity and high-performance power control algorithm is urgently required.

Motivated by the above observations, we investigate the power control problem for the UAV-assisted access networks with D2D communications, where a UAV acting as aerial BS provides wireless service for multiple users, and others are engaged in D2D transmissions. The main contributions are summarized as follows:

- We first formulate the power control optimization with the aim of maximizing the sum throughput under the transmit power budget, while considering the mutual interference among the UAV and D2D pairs.
- We then propose a successive convex algorithm to address the formulated optimization by leveraging D.C. (difference of two convex functions) programming, where the non-convex optimization problem is solved by iteratively addressing a series of convex optimization problems.
- We further design a low-complexity power control (L-PC) approach by analyzing the special structure of Hessian matrix for the application of the UAV. Moreover, the algorithm convergence is proved.

Our investigated scenario is different from the underlay cognitive radio network (CRN) although there are some common things [29]–[34]. In particular, all the users share the same spectrum in both cases. The differences are as follows: i) In CRN, the operating parameters of the primary user are generally fixed or pre-determined, which can not be influenced by the cognitive user according to the regulation rules [32]–[34]. The system is optimized mostly from the cognitive user perspective. Differently, in our work, the transmit power of the UAV user is adjusted to improve the system performance while satisfying its throughput requirement. In other words, there is cooperation among all the users; ii) the traditional CRN focuses on the ground-to-ground communications, whereas the air-to-ground communications are also considered besides the ground-to-ground communications.

The layout of this paper is organized as follows. The investigated scenario and optimization problem are presented in Section II. Then, we propose a power control algorithm by leveraging D.C. programming and a low-complexity power control algorithm in Section III and IV, respectively. In Section V, simulation results are provided to verify the effectiveness of the proposed algorithms. Finally, Section VI provides concluding remarks.

II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider a network where a number of users are randomly distributed, and a UAV is deployed to serve the terrestrial users. As shown in Fig. 1, some users receive the information signals from the UAV, namely UAV users (UUs). Meanwhile, multiple interfering D2D transmitters (D2D-Txs) transmit information signals to their corresponding receivers simultaneously. The distance between D2D pairs is generally much smaller than the case that the user communicates with ground base stations or other access points, which means better channel state. In campuses and sport stadiums, either UAV or D2D may be difficult to provide satisfactory services for many

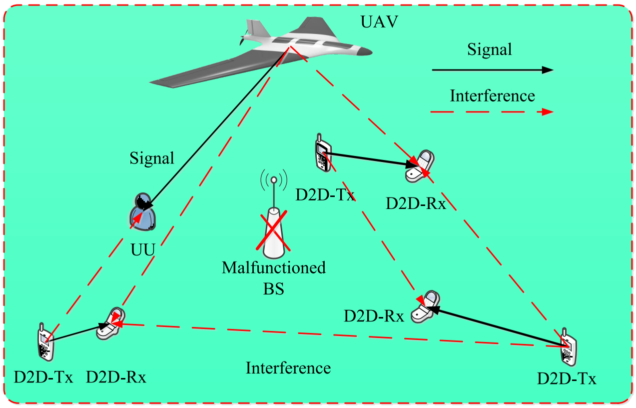

FIGURE 1. Investigated scenario of D2D communications underlaying UAV-assisted access networks.

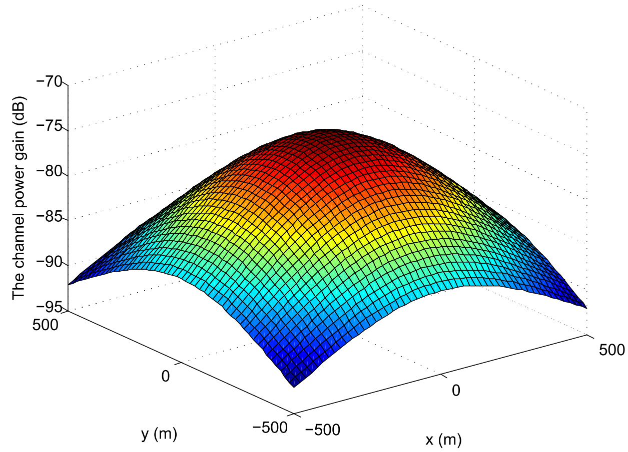

FIGURE 2. The channel power gain from the UAV to the UU with various locations, where $a = 11.95$, $b = 0.136$, $\alpha_u = 3$, $\eta = 20$ dB, $h = 300$ m.

users at the same time. In this case, some users communicate with the UAV while others are able to communicate directly, which provides the throughput gains. Orthogonal frequency division multiple access (OFDMA) is designed for multiple UUs, and each sub-channel used by one UU can serve multiple D2D pairs. We focus on the power control problem assuming that the spectrum resource allocation has been accomplished. The UAV hovers over the origin with the altitude h. Since all the users share the same spectrum, the UUs receive the interference signals from all D2D-Txs.

Denote $\mathcal{N} = \{1, 2, \ldots, n, \ldots, N\}$ as the set of D2D pairs, p_0 and p_n as the transmit powers of the UAV and n-th D2D-Tx, respectively. We collect all transmit power into one vector $\mathbf{p}$, i.e., $\mathbf{p} = \{p_0, p_1, \ldots, p_N\}$. Denote $g_U(x, y)$ as the channel power gain from the UAV to the UU at (x, y), $g_{n,n}$ as the channel power gain from the n-th D2D-Tx to its D2D-Rx. The channel power gain of the interference link from the n-th D2D-Tx to the UU located at (x, y) is $\tilde{g}_n(x, y)$. The communication channel between D2D-Tx and D2D-Rx is modeled as $g_n = \beta_0 \rho_n^2 D^{-\alpha}$, where β_0 is the channel power gain at the reference distance d_0, ρ_n^2 is an exponentially distributed random variable with unit mean, α is the path loss exponent for D2D link, and D is the distance between the D2D-Tx and D2D-Rx. The ATG channel is characterized by LOS and NLOS links independently with corresponding probabilities of occurrence [9]–[11]. Specifically, $g_U(x, y)$ is given by

$$g_U(x, y) = \begin{cases} \left(\sqrt{x^2 + y^2 + h^2}\right)^{-\alpha_u}, & LOS \text{ link}, \\ \eta\left(\sqrt{x^2 + y^2 + h^2}\right)^{-\alpha_u}, & NLOS \text{ link}, \end{cases} \tag{1}$$

where α_u is the path loss exponent for UAV-user links, and the term η represents the attenuation resulting from the NLOS connection. The probability of having LOS link depends on the locations of the UAV and the UU, the environment parameters, and elevation angle θ. It can be approximated by the following form [17]:

$$\Pr_{LOS} = \frac{1}{1 + a \exp(-b[\theta - a])}, \tag{2}$$

where constants a and b are the environment parameters, and elevation angle θ (measured in "degree") is calculated as

$$\theta = \frac{180}{\pi} \times \sin^{-1}\left(\frac{h}{\sqrt{x^2 + y^2 + h^2}}\right). \tag{3}$$

Thus, the probability of having NLOS link is $\Pr_{NLOS} = 1 - \Pr_{LOS}$. Finally, $g_U(x, y)$ is given by:

$$g_U(x, y) = \Pr_{LOS} \times \left(\sqrt{x^2 + y^2 + h^2}\right)^{-\alpha_u} + \Pr_{NLOS} \times \eta\left(\sqrt{x^2 + y^2 + h^2}\right)^{-\alpha_u}. \tag{4}$$

The channel gain $\tilde{g}_{U,n}$ of the interference link from the UAV to n-th D2D-Rx is similar with above mentioned UAV-user link. Fig. 2 displays the channel power gain with various UU locations. When the altitude of the UAV is fixed, we can see in Fig. 2 that the channel power gain relies on the distance between the UAV and the UU.

Furthermore, the signal to interference plus noise ratio (SINR) received at the UU is as

$$\gamma_{UU} = \frac{p_0 g_U(x, y)}{\sum_{n=1}^{N} p_n \tilde{g}_n(x, y) + \sigma^2}, \tag{5}$$

where σ^2 is the system noise power. Moreover, the SINR received at the n-th D2D-Rx is

$$\gamma_n = \frac{p_n g_{n,n}}{\sum_{m \in \mathcal{N}, m \neq n} p_m \tilde{g}_{m,n} + p_0 \tilde{g}_{U,n} + \sigma^2}, \tag{6}$$

where $\tilde{g}_{U,n}$ is the interference from the UAV to the n-th D2D-Rx. The system throughput of D2D pairs underlaying UAV-assisted access networks is thus given by

$$f(\mathbf{p}) = \sum_{n=1}^{N} \log_2(1+\gamma_n). \tag{7}$$

The aim of this paper is to maximize the sum throughput of D2D pairs via finding the optimal power, while satisfying the UU's minimum data rate requirement. Mathematically, the optimization can be written as:

$$\begin{aligned}\max_{\mathbf{p}=\{p_0,p_1,\ldots,p_N\}} & f(\mathbf{p}) \\ s.t.\ & C1: \log_2(1+\gamma_{UU}) \geq R_{\min}, \\ & C2: 0 \leq p_n \leq p_n^{\max}, \quad \forall n, \\ & C3: 0 \leq p_0 \leq p_0^{\max}, \end{aligned} \tag{8}$$

where $p_n^{\max}$ is the maximum transmit power of the n-th D2D-Tx, $p_0^{\max}$ and $R_{\min}$ are the maximum transmit power of the UAV and the required data rate of the UU, respectively. C1 ensures that the acquired throughput of the UU is not less that the required. C2 and C3 provide the transmit power limits for the UAV and D2D pairs. Notably, the requirement of UU is considered since D2D communications occupy the spectrum band licensed by the UU.

Remark 1: The optimization problem in (8) is different from the state-of-the-art studies for the following considerations: i) it is a non-convex optimization due to the mutual interference among all users, which cannot be solved directly by standards convex techniques, and ii) a fast power control algorithm is required since the UAV is changing the topology of the networks frequently over time and has limited computational capability.

III. POWER CONTROL BY USING D.C. PROGRAMMING

In this section, a successive convex algorithm is developed to address the formulated optimization in (8). Specifically, by analyzing the problem structure, it is shown that the non-convex optimization problem in (8) can be solved by iteratively addressing a series of convex problems. Then, the IPM is used to resolve these convex optimization problems [35].

The constraint $C1$ in (8) can be transformed into the following equivalent expression:

$$C1: \sum_{n=1}^{N} p_n \tilde{g}_n(x,y) \leq p_0 g_U(x,y) \Big/ \left(2^{R_{\min}}-1\right) - \sigma^2. \tag{9}$$

Therefore, all the constraints in (8) are convex. However, even with convex constraint $C1$, the optimization problem is still difficult to be directly solved since the objective in (8) is non-convex.

Note that the objective is the difference of two functions:

$$f(\mathbf{p}) = l(\mathbf{p}) - h(\mathbf{p}), \tag{10}$$

where

$$\begin{aligned} l(\mathbf{p}) &= \sum_{n=1} \log_2\left(\sum_{m=1} p_m g_{m,n} + p_0 \tilde{g}_{U,n} + \sigma^2\right), \\ h(\mathbf{p}) &= \sum_{n=1} \log_2\left(\sum_{m\in\mathcal{N}, m\neq n} p_m \tilde{g}_{m,n} + p_0 \tilde{g}_{U,n} + \sigma^2\right). \end{aligned} \tag{11}$$

$l(\mathbf{p})$ and $h(\mathbf{p})$ are concave functions. Therefore, the resulting function $l(\mathbf{p}) - h(\mathbf{p})$ is the D.C..

Theorem 1: A series of non-decreasing solutions $\{\mathbf{p}^{k+1}\}$ to (8) can be acquired by iteratively solving the following optimization:

$$\begin{aligned} \max_{\mathbf{p}} & f(\mathbf{p},\mathbf{p}') = l(\mathbf{p}) - \left(h(\mathbf{p}') + \langle \nabla h(\mathbf{p}'), \mathbf{p}-\mathbf{p}'\rangle\right) \\ s.t.\ & C1, \quad C2,\ C3, \end{aligned} \tag{12}$$

where the n-th component of the $\nabla h(\mathbf{p}')$ is derived as

$$\nabla h(\mathbf{p}') = \begin{cases} \displaystyle\sum_{k\in\mathcal{N},k\neq n} \frac{g_{n,k}}{\sum_{m\in\mathcal{N},m\neq k} p_m' \tilde{g}_{m,k} + p_0' \tilde{g}_{U,k} + \sigma^2} \frac{1}{\ln 2}, & n \neq 0, \\ \displaystyle\sum_{k\in\mathcal{N}} \frac{\tilde{g}_{U,k}}{\sum_{m\in\mathcal{N},m\neq k} p_m' \tilde{g}_{m,k} + p_0' \tilde{g}_{U,k} + \sigma^2} \frac{1}{\ln 2}, & n = 0, \end{cases} \tag{13}$$

and $\mathbf{p}' = \mathbf{p}^k$.

Proof: Because $l(\mathbf{p})$ and $h(\mathbf{p})$ are concave functions, there is $h(\mathbf{p}) \leq h(\mathbf{p}') + \langle \nabla h(\mathbf{p}'), \mathbf{p}-\mathbf{p}'\rangle$, which means $f(\mathbf{p}) = l(\mathbf{p}) - h(\mathbf{p}) \geq l(\mathbf{p}) - \left(h(\mathbf{p}') + \langle \nabla h(\mathbf{p}'), \mathbf{p}-\mathbf{p}'\rangle\right) = f(\mathbf{p},\mathbf{p}')$. Therefore, $f(\mathbf{p},\mathbf{p}')$ provides a tight low bound for the original objective function $f(\mathbf{p})$. Moreover, as $\mathbf{p}^{k+1}$ is the optimal solution to (12), there is

$$\begin{aligned} f\left(\mathbf{p}^{k+1}\right) &= l\left(\mathbf{p}^{k+1}\right) - h\left(\mathbf{p}^{k+1}\right) \\ &\geq l\left(\mathbf{p}^{k+1}\right) - \left(h(\mathbf{p}') + \left\langle \nabla h(\mathbf{p}'), \mathbf{p}^{k+1}-\mathbf{p}'\right\rangle\right) \\ &= \max_{\mathbf{p}}\ l(\mathbf{p}) - \left(h(\mathbf{p}') + \langle \nabla h(\mathbf{p}'), \mathbf{p}-\mathbf{p}'\rangle\right) \\ &\geq l(\mathbf{p}') - h(\mathbf{p}') = f\left(\mathbf{p}^k\right), \end{aligned} \tag{14}$$

which indicates we can get a series of non-decreasing solutions. ■

Since the value must be upper bounded by the optimal solution to (8), the sequence $\{\mathbf{p}^{k+1}\}$ always converges to a suboptimal solution [36].

Denote $\lambda_{th} = g_U(x,y) / \left(2^{R_{\min}}-1\right)$, we can get the barrier function of (12) as [35]:

$$\begin{aligned} \phi(\mathbf{p}) = &- \sum_{n=0}^{N} \log p_n - \sum_{n=0}^{N} \log\left(p_n^{\max} - p_n\right) \\ &- \log\left(p_0\lambda_{th} - \sigma^2 - \sum_{n=1}^{N} p_n \tilde{g}_n(x,y)\right). \end{aligned} \tag{15}$$

Therefore, the optimal solution to (12) can be acquired by addressing the following unconstrained minimization problem

$$\min \varphi(\mathbf{p},\mathbf{p}') = -tf(\mathbf{p},\mathbf{p}') + \phi(\mathbf{p}), \tag{16}$$

which can be efficiently solved via Newton's method. The parameter t determines the accuracy. The transmit power at $l+1$ iteration in Newton's method update according the following equation:

$$\mathbf{p}^{l+1} = \mathbf{p}^l + s\Delta_{nt}, \tag{17}$$

Algorithm 1 Backtracking Line Search

Initialization: Given a descent direction Δ_{nt} for φ at $\mathbf{p}$, $\alpha \in (0, 0.5)$, $\beta \in (0, 1)$
$s = 1$
While $\varphi\left(\mathbf{p} + s\Delta_{nt}\right) > \varphi\left(\mathbf{p}\right) + \alpha s \nabla\varphi(\mathbf{p})^T \Delta_{nt}$
$s = \beta s$

where Δ_{nt} is the Newton step and s is the step size obtained by the backtracking line search shown in Algorithm 1.

The calculation of Newton step Δ_{nt} is one of vital steps in Newton's method. To this end, the gradient $g = \nabla\varphi\left(\mathbf{p}, \mathbf{p}'\right)$ should be first derived and then we can establish Hessian matrix $H = \nabla^2\varphi\left(\mathbf{p}, \mathbf{p}'\right)$. For the n-th D2D pair, there is

$$g|_{p_n} = -t\frac{1}{\ln 2}\left(\sum_{k=1} J_k^n - \sum_{k=1,k\neq n} R_k^n\right) - \frac{1}{p_n} + \frac{1}{p_n^{\max} - p_n} + \frac{\tilde{g}_n\left(x, y\right)}{p_0\lambda_{th} - \sigma^2 - \sum_{n=1} p_n\tilde{g}_n\left(x, y\right)}, \tag{18}$$

and the first-order derivative with $n = 0$ is

$$g|_{p_U} = -t\frac{1}{\ln 2}\left(\sum_{k=1} J_k^0 - \sum_{k=1} R_k^0\right) - \frac{1}{p_0} + \frac{1}{p_0^{\max} - p_0} - \frac{\lambda_{th}}{p_0\lambda_{th} - \sigma^2 - \sum_{n=1} p_n\tilde{g}_n\left(x, y\right)}, \tag{19}$$

where

$$\begin{aligned} J_k^n &= \frac{g_{n,k}}{\sum_{m=1} p_m g_{m,k} + p_0\tilde{g}_{U,k} + \sigma^2}, \\ R_k^n &= \frac{g_{n,k}}{\sum_{m\neq k} p_m{}'\tilde{g}_{m,k} + p_0{}'\tilde{g}_{U,k} + \sigma^2}, \\ J_k^0 &= \frac{\tilde{g}_{U,k}}{\sum_{m=1} p_m g_{m,k} + p_0\tilde{g}_{U,k} + \sigma^2}, \\ R_k^0 &= \frac{\tilde{g}_{U,k}}{\sum_{m\neq k} p_m{}'\tilde{g}_{m,k} + p_0{}'\tilde{g}_{U,k} + \sigma^2}. \end{aligned} \tag{20}$$

Consequently, the (n, m)-th element of Hessian matrix is given by (21) at the top of next page. Then, the Newton step Δ_{nt} can be obtained by solving $H\Delta_{nt} = -g$. The whole procedure for solving (8) is shown in Algorithm 2.

The proposed successive convex algorithm includes three-tier iterations. The outer iteration is the power update procedure defined by solving the problem in (12). The inner iterations are IPM and Newton's method, respectively. The complexity can be evaluated roughly as follows. The computation of Newton step (i.e., Step 7 in Algorithm 2) occupies the leading position, which needs float operations and has the complexity of $O(N^3)$. The iteration numbers of three-tier iterations are assumed to be K_1, K_2, K_3 in the power control algorithm. Therefore, the complexity characterizing the total computations is estimated as $O(K_1K_2K_3N^3)$.

Algorithm 2 Proposed Power Control Algorithm

1: Initialize the parameters $\mathbf{p}^{(0)} = \{p_n^0\}$, $t = t^{(0)} > 0$, $\mu > 1$, ε_1, ε_2
2: **Repeat**
3: $t = t^{(0)} > 0$
4: **Repeat**
5: Set $\mathbf{p}^k$ as an initial point, minimize $\varphi\left(\mathbf{p}, \mathbf{p}'\right)$
6: **Repeat**
7: Compute Newton step Δ_{nt} using (18), (19), (21) and Newton decrement $\lambda^2 = -g^T\Delta_{nt}$
8: Find step size s by backtracking line search
9: **Until** some termination condition is met
10: Update $\mathbf{p}^l = \mathbf{p}^*(c)$ and $t = \mu t$
11: **Until** $\left(2N + 1\right)/t < \varepsilon_2$
12: Update $\mathbf{p}^{k+1} = \mathbf{p}^*(c)$
13: **Until** $\left|f(\mathbf{p}^{k+1}) - f(\mathbf{p}^k)\right| \leq \varepsilon_1$
14: Return the optimal power $\mathbf{p}^{k+1}$

IV. LOW-COMPLEXITY POWER CONTROL ALGORITHM

The formulated optimization in (8) can be solved by leveraging successive convex approximation. Nevertheless, its high complexity $O(K_1K_2K_3N^3)$ hinders its applications in practical systems, especially for UAV-involved scenarios. Therefore, a low-complexity and high-performance approach is urgently required.

A. PROPOSED LOW-COMPLEXITY APPROACH

It can be observed that the main computations result from acquiring the Newton step Δ_{nt}, which needs to solve equation $H\Delta_{nt} = -g$ with high complexity of $O(N^3)$. Generally, Δ_{nt} is obtained using inverse operation, ignoring its potential characteristics, such as symmetry and positive definiteness. In [37] and [38], Wang *et al.* propose a fast IPM considering the low rank and diagonal feature of Hessian matrix H. However, the problem of interest in this paper do not possess these features. Next, we will study the relationship between the investigated power control problem and Hessian matrix.

Denote

$$\begin{aligned} X_k\left(n, m\right) &= \frac{g_{n,k}g_{m,k}}{\left(\sum_{m=1} p_m g_{m,k} + p_0\tilde{g}_{U,k} + \sigma^2\right)^2}, \\ Y\left(n, m\right) &= \frac{\tilde{g}_n\left(x, y\right)\tilde{g}_m\left(x, y\right)}{\left(p_0\lambda_{th} - \sigma^2 - \sum_{n=1} p_n\tilde{g}_n\left(x, y\right)\right)^2}. \end{aligned} \tag{22}$$

Then, we have the following result

$$\begin{aligned} &\sum_{k=1} X_k\left(n, m\right) \\ &\overset{(a)}{=} \sum_{k=1} \frac{1}{\left(\sum_{m=1} p_m\sqrt{\frac{g_{m,k}}{g_{n,k}}} + \left(p_0\tilde{g}_{U,k} + \sigma^2\right)\Big/\sqrt{g_{n,k}g_{m,k}}\right)^2} \\ &\overset{(b)}{<} \sum_{k=1} \frac{1}{\left(\sum_{m=1} p_m\sqrt{g_{m,k}\big/g_{n,k}}\right)^2}, \end{aligned} \tag{23}$$

$$H(n,m)=\begin{cases} t\frac{1}{\ln 2}\sum_{k\in\mathcal{N}}\frac{\tilde{g}_{U,k}\tilde{g}_{U,k}}{\left(\sum_{m=1}p_m g_{m,k}+p_0\tilde{g}_{U,k}+\sigma^2\right)^2}+\frac{\lambda_{th}\lambda_{th}}{\left(p_0\lambda_{th}-\sigma^2-\sum_{n=1}p_n\tilde{g}_n(x,y)\right)^2}+\frac{1}{p_0{}^2}+\frac{1}{\left(p_0^{\max}-p_0\right)^2}, \\ \quad n=m=1, \\ t\frac{1}{\ln 2}\sum_{k\in\mathcal{N}}\frac{\tilde{g}_{U,k}g_{m,k}}{\left(\sum_{m=1}p_m g_{m,k}+p_0\tilde{g}_{U,k}+\sigma^2\right)^2}-\frac{\lambda_{th}\tilde{g}_n(x,y)}{\left(p_0\lambda_{th}-\sigma^2-\sum_{n=1}p_n\tilde{g}_n(x,y)\right)^2}, \\ \quad n=1,\ m\neq 1 \text{ or } n\neq 1,\ m=1, \\ t\frac{1}{\ln 2}\sum_{k\in\mathcal{N}}\frac{g_{n,k}g_{m,k}}{\left(\sum_{m=1}p_m g_{m,k}+p_0\tilde{g}_{U,k}+\sigma^2\right)^2}+\frac{\tilde{g}_n(x,y)\,\tilde{g}_m(x,y)}{\left(p_0\lambda_{th}-\sigma^2-\sum_{n=1}p_n\tilde{g}_n(x,y)\right)^2}+\frac{1}{p_n{}^2}+\frac{1}{\left(p_n^{\max}-p_n\right)^2}, \\ \quad n\neq 1,\ m\neq 1,\ n=m, \\ t\frac{1}{\ln 2}\sum_{k\in\mathcal{N}}\frac{g_{n,k}g_{m,k}}{\left(\sum_{m=1}p_m g_{m,k}+p_0\tilde{g}_{U,k}+\sigma^2\right)^2}+\frac{\tilde{g}_n(x,y)\,\tilde{g}_m(x,y)}{\left(p_0\lambda_{th}-\sigma^2-\sum_{n=1}p_n\tilde{g}_n(x,y)\right)^2}, \\ \quad n\neq 1,\ m\neq 1,\ n\neq m. \end{cases} \tag{21}$$

where (a) is obtained by dividing the numerator and denominator with $g_{n,k}g_{m,k}$ and (b) is established by ignoring the interference from the UU and noise. Therefore, we have the following observations:

- When the transmit power of the n-th D2D-Tx approaches its maximum power, there is $\frac{1}{\left(p_n^{\max}-p_n\right)^2}\to\infty$. which means that $\sum_{k\in\mathcal{N}}1/\left(\sum_{m=1}p_m\sqrt{g_{m,k}/g_{n,k}}\right)^2 \ll 1/\left(p_n^{\max}-p_n\right)$.
- In the case of low transmit power or $p_n\to 0$, we have $1/p_n{}^2\to\infty$. Thus, there is $\sum_{k\in\mathcal{N}}1\Big/\left(\sum_{m=1}p_m\sqrt{g_{m,k}/g_{n,k}}\right)^2 \ll 1/p_n{}^2$.
- If the transmit power of m-th D2D-Tx is much smaller than that of the n-th D2D-Tx, there is $\sum_{k\in\mathcal{N}}1\Big/\left(\sum_{m=1}p_m\sqrt{g_{m,k}/g_{n,k}}\right)^2 \ll 1/p_m{}^2$.

As a result, it is found that the term $\sum_{k=1}X_k(n,m)$ is much smaller compared to other terms if there exist a D2D-Tx with high transmit power. One problem is to study the existence of D2D pairs with high transmit power in UAV-assisted access networks. In the sequel, we consider two scenarios: sparse networks and dense networks. In a sparse network, some D2D-Txs transmit the information with strong power since it only brings slight interference to others. However, in a dense network, the transmit powers of D2D-Txs are generally lower so as to not influence other users. Next, we detailed discuss the dense network scenario.

Deriving an analytical treatment is challenging due to the complicated optimization problem in (8). To this end, we resort to the following *arithmetic-geometric means inequality* [39]:

Lemma 1: For positive values $x_1,\ldots,x_N$,

$$G_N=\left(\prod_{n=1}^{N}x_n\right)^{\frac{1}{N}}\le\frac{1}{N}\sum_{n=1}^{N}x_n=A_N, \tag{24}$$

where A_N and G_N are arithmetic mean and geometric mean, respectively. The equality in (24) holds true if and only if $x_1=x_2=\ldots=x_N$.

Following above inequality, we have

$$\begin{aligned} f(\mathbf{p}) &= \log_2\left(\prod_{n=1}^{N}1+\frac{p_n g_{n,n}}{\sum_{m\in\mathcal{N},m\neq n}p_m\tilde{g}_{m,n}+p_0\tilde{g}_{U,n}+\sigma^2}\right) \\ &\le N\log_2\left(1+\frac{1}{N}\sum_{n=1}^{N}\frac{p_n g_{n,n}}{\sum_{m\neq n}p_m\tilde{g}_{m,n}+p_0\tilde{g}_{U,n}+\sigma^2}\right). \end{aligned} \tag{25}$$

The interference is usually serious in a dense network, which thus results in *low-SINR*. In this context, we can use the right hand of inequality in (25) to approximate the objective as follows:

$$f(\mathbf{p})\approx N\log_2\left(1+\frac{1}{N}\sum_{n=1}^{N}\frac{p_n g_{n,n}}{\sum_{m\neq n}p_m\tilde{g}_{m,n}+p_0\tilde{g}_{U,n}+\sigma^2}\right). \tag{26}$$

As the log-function is monotonically increasing, we focus on the function $R(\mathbf{p})=1+1/N\sum_{n=1}^{N}\left(p_n g_{n,n}\Big/\sum_{m\neq n}p_m\tilde{g}_{m,n}+p_0\tilde{g}_{U,n}+\sigma^2\right)$ in the sequel. For each D2D pair, there is

$$\frac{\partial^2 R(\mathbf{p})}{\partial p_n{}^2}=\frac{1}{N}\sum_{n\neq k}^{N}\frac{2p_n g_{n,n}g_{n,k}{}^2}{\left(\sum_{m\neq n}p_m\tilde{g}_{m,n}+p_0\tilde{g}_{U,n}+\sigma^2\right)^3}. \tag{27}$$

This means that if the transmit power of a D2D-Tx doesn't reach its maximum or minimum, there always exist a solution with $R(\mathbf{p}')\ge R(\mathbf{p})$ such that one more D2D pair reach its endpoint. As a result, there is at least one D2D pair with maximum transmit power in a dense network.

Theorem 2: Denote $z\triangleq\max\frac{1+\gamma_n}{1+\gamma_m}$. The difference between the approximate objective function in Eq. (26) and the original objective function in Eq. (25) approaches 0 with $z\to 1$.

Proof: See Appendix for the proof. ■

From above analysis, we see that there always exist at least one D2D pair with strong transmit power, which means that $\sum_{k=1} X_k(n,m)$ is much smaller than other terms. As a result, we design a low-complexity power control algorithm, i.e., approximate the Hessian matrix with Eq. (28), as shown at the top of the next page.

Remark 2: Notice that in practical networks, there may be no user with high transmit power. In this case, $\sum_{k=1} X_k(n,m)$ cannot be ignored. We will show in the later that whatever the value $\sum_{k=1} X_k(n,m)$ is, the convergence of the proposed algorithm can always be guaranteed. However, this value will affect the accuracy of the approximation. In order to maintain more matrix information, the first items $t/\ln 2 \sum_{k=1} X_k(n,m)$ of the non-diagonal elements are discarded, whereas these terms of diagonal elements in Hessian matrix are all preserved. When Hessian matrix is approximated by Eq. (28), the method proposed in [37] can be used to reduce the complexity of computing Newton step.

The approximate Hessian matrix is expressed as follows

$$H^a = \begin{bmatrix} H_1 & & & \\ & H_2 & & \\ & & \ddots & \\ & & & H_{N+1} \end{bmatrix} + \begin{bmatrix} \nabla b_1 \nabla b_1 & \cdots & \cdots & \nabla b_1 \nabla b_{N+1} \\ \vdots & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ \nabla b_{N+1} \nabla b_1 & \cdots & \cdots & \nabla b_{N+1} \nabla b_{N+1} \end{bmatrix} \triangleq H_d + \nabla b \nabla b^T, \tag{29}$$

with

$$\nabla b = \frac{\left[\lambda_{th}, -\tilde{g}_1(x,y), \ldots, -\tilde{g}_N(x,y)\right]^T}{p_0 \lambda_{th} - \sigma^2 - \sum_{n=1} p_n \tilde{g}_n(x,y)}, \tag{30a}$$

$$H_n = t\frac{1}{\ln 2}\sum_{k\in\mathcal{N}} X_k(n,n) + \frac{1}{p_n{}^2} + \frac{1}{\left(p_n^{\max} - p_n\right)^2}. \tag{30b}$$

The following Lemma characters the approximate Hessian matrix.

Lemma 2: The approximate Hessian matrix H^a is positive definite. *Proof:* Since H_d is diagonal and there is $H_n > 0$, H_d is positive definite. Moreover, considering that $\nabla b \nabla b^T$ is positive semidefinite, $H^a = H_d + \nabla b \nabla b^T$ is positive definite. ■

From Lemma 2, we can see that the approximate Hessian matrix is also invertible. Therefore, the Newton step can be obtained by solving

$$\left(H_d + \nabla b \nabla b^T\right) \Delta_{nt} = -g. \tag{31}$$

Since H^a is positive define and invertible [37], we have

$$\Delta_{nt} = \left(H_d + \nabla b \nabla b^T\right)^{-1}(-g). \tag{32}$$

Using the matrix inversion Lemma [40], we have

$$\Delta_{nt} = H_d{}^{-1}(-g) - \frac{H_d{}^{-1}\nabla b\,(-g)\,\nabla b^T H_d{}^{-1}}{1 + \nabla b^T H_d{}^{-1} \nabla b}. \tag{33}$$

The Δnt can be calculated as follows. We first evaluate $z = H_d{}^{-1}(-g)$. Then, we get the value $E = 1 + \nabla b^T H_d{}^{-1} \nabla b$. Next we solve $Ew = \nabla bz$. Finally, we evaluate $\Delta_{nt} = z - H_d{}^{-1} \nabla bw$. The total complexity is about $O(N)$

Complexity Analysis: To obtain the Newton step Δ_{nt}, N computations should be conducted to solve $H\Delta_{nt} = -g$. The iteration numbers of three-tier iterations are given as L_1, L_2, L_3 in the proposed L-PC algorithm. Then, the complexity characterizing the total computations is estimated as $O(L_1 L_2 L_3 N)$. Therefore, the proposed algorithm is attractive for the application of the UAV communications.

B. CONVERGENCE ANALYSIS

Theorem 3: Approximating Hessian matrix by (28) in algorithm 2, the proposed low-complexity power control (L-PC) approach can always converge to a suboptimal solution.

Proof: To proof the algorithm convergence, we first introduce the Lemma 3 [35].

Lemma 3: For a strongly convex function f, there exists an $m > 0$ such that $\nabla^2 f \succeq mI$. Then, we have

$$U \geq f(x) - \frac{1}{2m}\|g\|^2, \tag{34}$$

where U is the optimal value and g is given by Eq. (18) and Eq. (19).

Because $\varphi(\mathbf{p}) = \varphi(\mathbf{p}, \mathbf{p}')$ given in (16) is a strongly convex function, there exist positive constants m and M such that $MI \succeq H \succeq mI$. The function $\varphi\left(\mathbf{p}^{k+1}\right)$ is upper bounded by:

$$\varphi\left(\mathbf{p}^k + s\Delta_{nt}\right) = \varphi\left(\mathbf{p}^k - sH^{-1}g\right) \leq \varphi\left(\mathbf{p}^k\right) - sg\left\|H^{-1}g\right\| + \frac{Ms^2}{2}\left\|H^{-1}g\right\|^2. \tag{35}$$

In the proposed L-PC approach, backtracking line search is applied. Next, we show that the condition

$$\varphi\left(\mathbf{p}^k - sH^{-1}g\right) \leq \varphi\left(\mathbf{p}^k\right) - \alpha sg\left\|H^{-1}g\right\| \tag{36}$$

is satisfied whenever $0 \leq s \leq 1/M$. Since $0 \leq s \leq 1/M$, there is $-s + Ms^2/2 \leq -s/2$. Considering the upper bound in (35), we have

$$\begin{aligned}\varphi\left(\mathbf{p}^{k+1}\right) &\leq \varphi\left(\mathbf{p}^k\right) - sg\left\|H^{-1}g\right\| + \frac{Ms^2}{2}\left\|H^{-1}g\right\|^2 \\ &\leq \varphi\left(\mathbf{p}^k\right) - (s/2)\,g\left\|H^{-1}g\right\|^2 \\ &\leq \varphi\left(\mathbf{p}^k\right) - \alpha sg\left\|H^{-1}g\right\|.\end{aligned} \tag{37}$$

Therefore, the backtracking line search will terminate if $s = 1$ or $s \geq \beta/M$, which limits the decrease of the objective

$$H^a(n,m)=\begin{cases} t\frac{1}{\ln 2}\sum_{k\in\mathcal{N}}\frac{\tilde{g}_{U,k}\tilde{g}_{U,k}}{\left(\sum_{m=1}p_m g_{m,k}+p_0\tilde{g}_{U,k}+\sigma^2\right)^2}+\frac{\lambda_{th}\lambda_{th}}{\left(p_0\lambda_{th}-\sigma^2-\sum_{n=1}p_n\tilde{g}_n(x,y)\right)^2}+\frac{1}{p_0{}^2}+\frac{1}{\left(p_0^{\max}-p_0\right)^2}, & n=m=1,\\ -\frac{\lambda_{th}\tilde{g}_n(x,y)}{\left(p_0\lambda_{th}-\sigma^2-\sum_{n=1}p_n\tilde{g}_n(x,y)\right)^2}, & n=1,\ m\neq 1 \text{ or } n\neq 1,\ m=1,\\ t\frac{1}{\ln 2}\sum_{k\in\mathcal{N}}\frac{g_{n,k}g_{m,k}}{\left(\sum_{m=1}p_m g_{m,k}+p_0\tilde{g}_{U,k}+\sigma^2\right)^2}+\frac{\tilde{g}_n(x,y)\tilde{g}_m(x,y)}{\left(p_0\lambda_{th}-\sigma^2-\sum_{n=1}p_n\tilde{g}_n(x,y)\right)^2}+\frac{1}{p_n{}^2}+\frac{1}{\left(p_n^{\max}-p_n\right)^2}, & n\neq 1,\ m\neq 1,\ n=m,\\ \frac{\tilde{g}_n(x,y)\tilde{g}_m(x,y)}{\left(p_0\lambda_{th}-\sigma^2-\sum_{n=1}p_n\tilde{g}_n(x,y)\right)^2}, & n\neq 1,\ m\neq 1,\ n\neq m. \end{cases} \tag{28}$$

function. For the case of $s=1$, we have

$$\varphi\left(\mathbf{p}^{k+1}\right)\leq\varphi\left(\mathbf{p}^{k}\right)-\alpha g\left\|H^{-1}g\right\|. \tag{38}$$

On the other hand, for the case of $s\geq\beta/M$, there is

$$\varphi\left(\mathbf{p}^{k+1}\right)\leq\varphi\left(\mathbf{p}^{k}\right)-\left(\alpha\beta/M\right)g\left\|H^{-1}g\right\|. \tag{39}$$

As a result, we have

$$\varphi\left(\mathbf{p}^{k+1}\right)\leq\varphi\left(\mathbf{p}^{k}\right)-\min\{\alpha,\alpha\beta/M\}g\left\|H^{-1}g\right\|. \tag{40}$$

Then, subtracting U from two sides, there is

$$\begin{aligned}&\varphi\left(\mathbf{p}^{k+1}\right)-U\\ &\leq\varphi\left(\mathbf{p}^{k}\right)-U-\min\{\alpha,\alpha\beta/M\}g\left\|H^{-1}g\right\|\\ &=\varphi\left(\mathbf{p}^{k}\right)-U-\min\{\alpha\left\|H^{-1}\right\|,\left\|H^{-1}\right\|\alpha\beta/M\}\|g\|^2.\end{aligned} \tag{41}$$

Based on the Lemma 3, we can get

$$\varphi\left(\mathbf{p}^{k+1}\right)-U\leq\left(\varphi\left(\mathbf{p}^{k}\right)-U\right)c, \tag{42}$$

where c is given by

$$c=\left(1-2m\min\{\alpha\left\|H^{-1}\right\|,\left\|H^{-1}\right\|\alpha\beta/M\}\right)<1. \tag{43}$$

Through the above procedure, we conclude

$$\varphi\left(\mathbf{p}^{k}\right)-U\leq\left(\varphi\left(\mathbf{p}^{0}\right)-U\right)c, \tag{44}$$

which means $\varphi\left(\mathbf{p}^{k}\right)$ can converges to U. ■

From the convergence proof, it can be seen that, no matter what the value of the term $\sum_{k=1}X_k(n,m)$ is, approximating the Hessian matrix with Eq. (28) can always guarantee the convergence of the proposed low-complexity power control algorithm.

Remark 3: The UAV-assisted access network is a dynamic system, which is characterized by a pseudo-static optimization in a slot-by-slot manner in this paper. Specifically, at each time slot, the number and requirements of D2D pairs, the channel state and the locations of all the users, *etc.*, are fixed and known. If the D2D topology is frequently changing, there may be dynamics between time slots. The optimized transmit power is obtained by performing the proposed algorithm, which would be rescheduled at each new time slot.

TABLE 1. System parameters.

Parameter	Value	Comments
σ_0^2	-130 dBm	Noise power
ε_1, ε_2	10^{-3}	Predefined accuracy
D	30 m	Distance of D2D pairs
$p_0^{\max}$	5 W	UAV's maximum transmit power
β_0	-30 dB	The channel power gain at d_0
α	2	Path loss exponent for D2D links
α_u	3	Path loss exponent for UAV-user links
a, b	11.95, 0.136	The parameters for urban environment
η	20 dB	The excessive attenuation factor
h	300 m	The altitude of the UAV

V. SIMULATIONS AND DISCUSSIONS

In this section, we present simulation results to demonstrate the effectiveness of the proposed algorithms. The main simulation parameters are set according to [17] and listed in Table I. The number of D2D pairs, rate requirement of the UU, and the maximum transmit power of the D2D-Txs vary according to specific simulation scenarios. Considering that the D2D pairs are randomly and uniformly located in a 1000 × 1000m square region. A UAV is located at the center of considered region to serve a UU, whose location is also random. The provided results are averaged on 100 independent realizations.

In Fig. 3, the convergence behavior of L-PC algorithm is shown, where the number of D2D pairs $N = 5$ and the maximum transmit power $p^{\max} = 100$ mW. As can be seen from the figure, the L-PC algorithm converges fast and about five iterations are performed. Moreover, we see that after two iterations, two D2D pairs reach maximum transmit

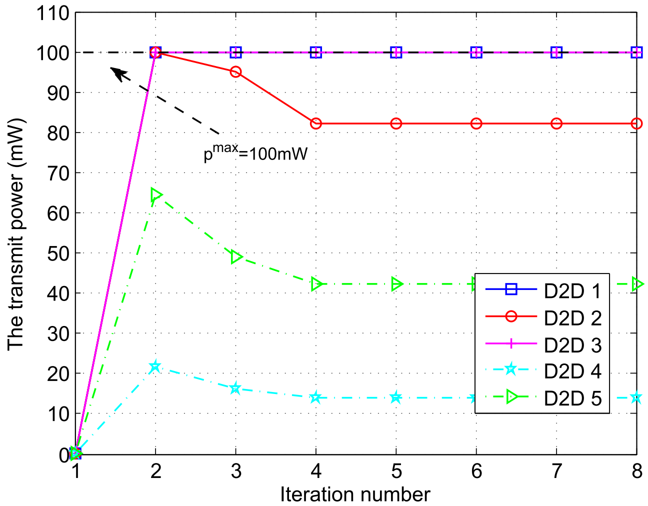

FIGURE 3. **The transmit power over the iteration number, where $N = 5$.**

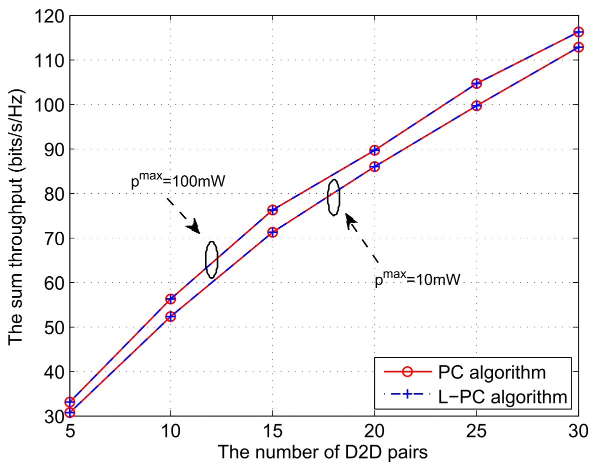

FIGURE 4. **The achievable sum throughput versus the number of D2D pairs.**

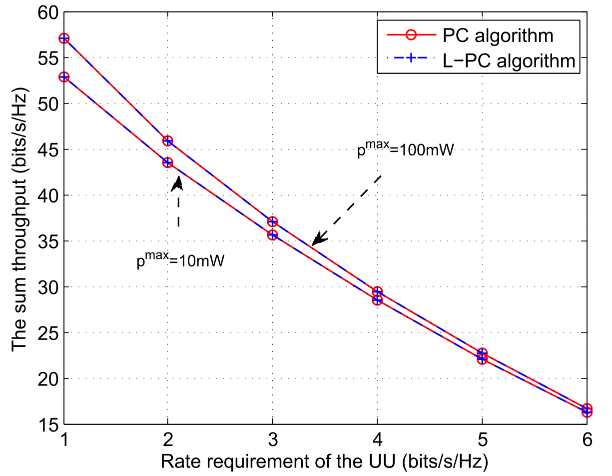

FIGURE 5. **The achievable sum throughput versus UU's rate requirement.**

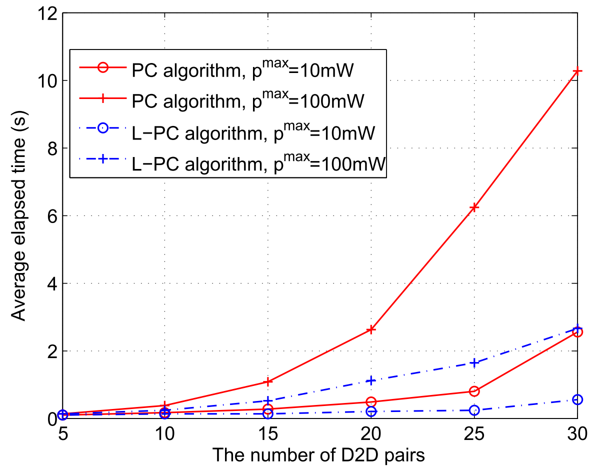

FIGURE 6. **Average elapsed time over the number of D2D pairs.**

power, while others decrease their power to reduce the mutual interference.

Fig. 4 depicts the achievable system throughput of proposed PC algorithm and L-PC approach along with varying transmit power limits. There are $p^{max} = 100$ mW and $p^{max} = 10$ mW in two cases, respectively. It is first observed that the throughput grows with the increasing number of D2D pairs for all settings. But the slopes gradually slow down since the serious interference prevents the throughput from linear growth. Furthermore, it can be found in Fig. 4 that the proposed algorithms achieve almost the same throughput for all scenarios, which verifies the effectiveness of the proposed L-PC algorithm. This is due to the fact that the approximation of Hessian matrix can always obtain a descent direction. Hence, the values will reduce over the iteration. Additionally, comparing the curves in Fig. 4, we can observe that the throughput performance can be improved with higher allowed transmit power.

To further evaluate the algorithm performance, the sum throughput of D2D pairs is plotted under different throughput requirements in Fig. 5. The number of D2D pairs is $N = 10$. Obviously, the throughput decreases with higher UU rate requirement. It is worth noticed that there are almost the same performance between the two algorithms with an increasing rate requirement of the UU. One interesting phenomenon is that the system throughput is little affected by the maximum transmit power in the case of high UU rate requirement. This stems from the fact that the high UU rate requirement imposes strict restriction on the transmit power and high transmit power is not allowed, which means the UU rate requirement dominates the throughput. Correspondingly, the constraint on maximum transmit power dominates the throughput in the case of low UU rate requirement.

Furthermore, we investigate the computational complexity of the proposed two power control algorithms in Fig. 6, which is characterized by the time elapsed counted by the *inbuilt* function *tic-toc* in Matlab. Observing the curve trend in Fig. 6, we see that the complexity of the L-PC algo-

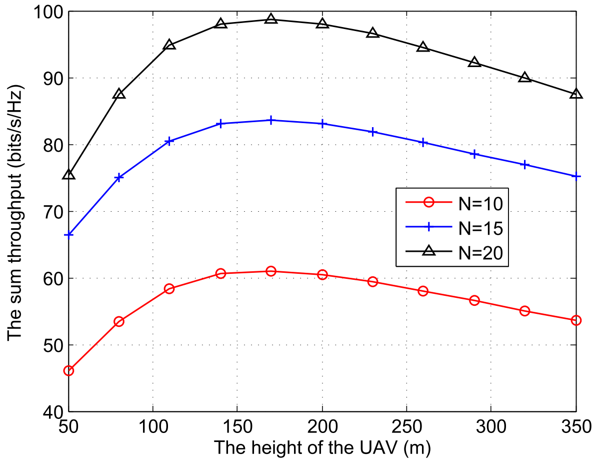

FIGURE 7. **The achievable sum throughput versus the height of the UAV.**

rithm is much lower than that of the PC algorithm. This benefits from the calculation of the Newton step with low complexity.

In Fig. 7, we illustrate the sum throughput with different heights of the UAV under various number of D2D pairs. It is shown that employing the UAV as a mobile BS can bring additional performance improvement by adjusting its height. Specifically, strong information signal between the UAV and UAV user generally means serious interference induced by the UAV, and vice versa. Morevoer, raising the height h not only increases the distance between the UAV and users, but also increases the probability of having LOS. Therefore, there exist an optimal height which provides a tradeoff for the received information signal and induced interference.

VI. CONCLUSION

In this paper, the power control optimization is studied for UAV-assisted access networks with D2D communications. We first proposed a PC algorithm to maximize the system throughput by leveraging D.C. programming. Considering the UAV's characteristic, i.e., limited energy and low computational capability, we then developed a L-PC algorithm. Simulation results validated the effectiveness of algorithms. For future work, mobile cases, such as the dynamics of the users and the flying UAV, are highly appreciated. Meanwhile, some scenarios that reflect the UAV's characteristic should be investigated.

APPENDIX
PROOF OF THEOREM 1

The difference between the original objective function in (24) and the approximate objective function in (25) is given by:

$$N\log_2\left(1+\frac{1}{N}\sum_{n=1}^{N}\frac{p_n g_{n,n}}{\sum_{m\neq n} p_m \tilde{g}_{m,n}+p_0\tilde{g}_{U,n}+\sigma^2}\right)$$

$$-\log_2\left(\prod_{n=1}^{N}1+\frac{p_n g_{n,n}}{\sum_{m\neq n} p_m \tilde{g}_{m,n}+p_0\tilde{g}_{U,n}+\sigma^2}\right)$$

$$=N\log_2\left(\frac{A_N}{G_N}\right). \tag{45}$$

Further, applying the Specht's ratio $S(z)$ [41], we have

$$\frac{A_N}{G_N}\leq S(z)\triangleq\frac{(z-1)\,z^{\frac{1}{z-1}}}{e\ln z}, \tag{46}$$

where $z\triangleq\max\frac{1+\gamma_n}{1+\gamma_m}$. So we have

$$0\leq\log_2\left(\frac{A_N}{G_N}\right)\leq\log_2\left(\frac{(z-1)\,z^{\frac{1}{z-1}}}{e\ln z}\right). \tag{47}$$

when $z\to 1$, the upper bound is

$$\lim_{z\to 1}\log_2\left(\frac{(z-1)\,z^{\frac{1}{z-1}}}{e\ln z}\right)$$

$$\underline{\underline{z=z+1}}\log_2\left(\lim_{z\to 0}\frac{z(1+z)^{\frac{1}{z}}}{e\ln(1+z)}\right)$$

$$=\log_2\left(\lim_{z\to 0}\frac{(1+z)^{\frac{1}{z}}}{e}\lim_{z\to 0}\frac{z}{\ln(1+z)}\right)=0. \tag{48}$$

When $z\to\infty$, there is

$$\lim_{z\to\infty}\log_2\left(\frac{(z-1)\,z^{\frac{1}{z-1}}}{e\ln z}\right)$$

$$=\log_2\left(\lim_{z\to\infty}\frac{z^{\frac{z}{z-1}}}{e\ln z}\right)=\log_2\left(\lim_{t\to 0}\frac{z}{e\ln z}\right)=\infty. \tag{49}$$

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REFERENCES

[1] H. Wang, G. Ding, J. Wang, S. Wang, and L. Wang, "Power control for multiple interfering D2D communications underlaying cellular networks: An approximate interior point approach," in *Proc. Int. Conf. Commun. Workshops (ICC Workshops)*, Paris, France, May 2017, pp. 1346–1351.

[2] Y. Zeng, R. Zhang, and T. J. Lim, "Wireless communications with unmanned aerial vehicles: Opportunities and challenges," *IEEE Commun. Mag.*, vol. 54, no. 5, pp. 36–42, May 2016.

[3] H. Wang, G. Ding, F. Gao, J. Chen, J. Wang, and L. Wang, "Power control in UAV-supported ultra dense networks: Communications, caching, and energy transfer," *IEEE Commun. Mag.*, vol. 56, no. 6, pp. 28–34, Jun. 2018.

[4] G. Ding, Q. Wu, L. Zhang, Y. Lin, T. A. Tsiftsis, and Y.-D. Yao, "An amateur drone surveillance system based on the cognitive Internet of Things," *IEEE Commun. Mag.*, vol. 56, no. 1, pp. 29–35, Jan. 2018.

[5] H. Wang, G. Ren, J. Chen, G. Ding, and Y. Yang, "Unmanned aerial vehicle-aided communications: Joint transmit power and trajectory optimization," *IEEE Wireless Commun. Lett.*, to be published.

[6] J. Lyu, Y. Zeng, and R. Zhang, "Cyclical multiple access in UAV-aided communications: A throughput-delay tradeoff," *IEEE Wireless Commun. Lett.*, vol. 5, no. 6, pp. 600–603, Dec. 2016.

[7] P. Zhan, K. Yu, and A. L. Swindlehurst, "Wireless relay communications with unmanned aerial vehicles: Performance and optimization," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 47, no. 3, pp. 2068–2085, Jul. 2011.

[8] Y. Zeng *et al.*, "Throughput maximization for UAV-enabled mobile relaying systems," *IEEE Trans. Commun.*, vol. 64, no. 12, pp. 4983–4996, Dec. 2016.
[9] Q. Feng, J. McGeehan, E. K. Tameh, and A. R. Nix, "Path loss models for air-to-ground radio channels in urban environments," in *Proc. IEEE Veh. Technol. Conf. (VTC)*, Melbourne, VIC, Australia, May 2006, pp. 2901–2905.
[10] J. Holis and P. Pechac, "Elevation dependent shadowing model for mobile communications via high altitude platforms in built-up areas," *IEEE Trans. Antennas Propag.*, vol. 56, no. 4, pp. 1078–1084, Apr. 2008.
[11] A. Al-Hourani, S. Kandeepan, and A. Jamalipour, "Modeling air-to-ground path loss for low altitude platforms in urban environments," in *Proc. IEEE Global Telecommun. Conf. (GLOBECOM)*, Austin, TX, USA, Dec. 2014, pp. 2898–2904
[12] A. Al-Hourani, S. Kandeepan, and S. Lardner, "Optimal LAP altitude for maximum coverage," *IEEE Wireless Commun. Lett.*, vol. 3, no. 6, pp. 569–572, Dec. 2014.
[13] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, "Drone small cells in the clouds: Design, deployment and performance analysis," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, San Diego, CA, USA, Dec. 2015, pp. 1–6.
[14] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, "Efficient deployment of multiple unmanned aerial vehicles for optimal wireless coverage," *IEEE Commun. Lett.*, vol. 20, no. 8, pp. 1647–1650, Aug. 2016.
[15] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, "Mobile Internet of Things: Can UAVs provide an energy-efficient mobile architecture?" in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Washington, DC, USA, Dec. 2016, pp. 1–6.
[16] V. Sharma, M. Bennis, and R. Kumar, "UAV-assisted heterogeneous networks for capacity enhancement," *IEEE Commun. Lett.*, vol. 20, no. 6, pp. 1207–1210, Jun. 2016.
[17] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, "Unmanned aerial vehicle with underlaid device-to-device communications: Performance and tradeoffs," *IEEE Trans. Wireless Commun.*, vol. 15, no. 6, pp. 3949–3963, Jun. 2016.
[18] C. Zhang and W. Zhang, "Spectrum sharing for drone networks," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 1, pp. 136–144, Jan. 2017.
[19] 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, Mar. 2018.
[20] G. Ding, J. Wang, Q. Wu, Y.-D. Yao, F. Song, and T. A. Tsiftsis, "Cellular-base-station-assisted device-to-device communications in TV white space," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 1, pp. 107–121, Jan. 2016.
[21] K. Doppler, M. Rinne, C. Wijting, C. B. Ribeiro, and K. Hugl, "Device-to-device communication as an underlay to LTE-advanced networks," *IEEE Commun. Mag.*, vol. 47, no. 12, pp. 42–49, Dec. 2009.
[22] A. Asadi, Q. Wang, and V. Mancuso, "A survey on device-to-device communication in cellular networks," *IEEE Commun. Surveys Tuts.*, vol. 16, no. 4, pp. 1801–1819, Nov. 2014.
[23] C.-H. Yu, O. Tirkkonen, K. Doppler, and C. Ribeiro, "Power optimization of device-to-device communication underlaying cellular communication," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Dresden, Germany, Jun. 2009, pp. 1–5.
[24] C.-H. Yu, K. Doppler, C. B. Ribeiro, and O. Tirkkonen, "Resource sharing optimization for device-to-device communication underlaying cellular networks," *IEEE Trans. Wireless Commun.*, vol. 10, no. 8, pp. 2752–2763, Aug. 2011.
[25] W. Zhao and S. Wang, "Resource allocation for device-to-device communication underlaying cellular networks: An alternating optimization method," *IEEE Commun. Lett.*, vol. 19, no. 8, pp. 1398–1401, Aug. 2015.
[26] D. Feng *et al.*, "Mode switching for energy-efficient device-to-device communications in cellular networks," *IEEE Trans. Wireless Commun.*, vol. 14, no. 12, pp. 6993–7003, Dec. 2015.
[27] H.-H. Nguyen *et al.*, "Distributed resource allocation for D2D communications underlay cellular networks," *IEEE Commun. Lett.*, vol. 20, no. 5, pp. 942–945, May 2016.
[28] Y. Li, D. Jin, J. Yuan, and Z. Han, "Coalitional games for resource allocation in the device-to-device uplink underlaying cellular networks," *IEEE Trans. Wireless Commun.*, vol. 13, no. 7, pp. 3965–3977, Jul. 2014.
[29] M. E. Tanab and W. Hamouda, "Resource allocation for underlay cognitive radio networks: A survey," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 2, pp. 1249–1276, 2nd Quart., 2017.
[30] A. G. Marques, L. M. Lopez-Ramos, G. B. Giannakis, and J. Ramos, "Resource allocation for interweave and underlay CRs under probability-of-interference constraints," *IEEE J. Sel. Areas Commun.*, vol. 30, no. 10, pp. 1922–1933, Nov. 2012.
[31] L. M. Lopez-Ramos, A. G. Marques, and J. Ramos, "Joint sensing and resource allocation for underlay cognitive radios," in *Proc. IEEE Int. Conf. Acoust. Speech Signal Process. (ICASSP)*, Florence, Italy, May 2014, pp. 7283–7287.
[32] B. Wang and D. Zhao, "Scheduling for long term proportional fairness in a cognitive wireless network with spectrum underlay," *IEEE Trans. Wireless Commun.*, vol. 9, no. 3, pp. 1150–1158, Mar. 2010.
[33] M. Elsaadany and W. Hamouda, "Energy efficient design for non-orthogonal AF relaying in underlay spectrum sharing networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Kuala Lumpur, Malaysia, May 2016, pp. 1–6.
[34] B. Wang, D. Zhao, and J. Cai, "Joint connection admission control and packet scheduling in a cognitive radio network with spectrum underlay," *IEEE Trans. Wireless Commun.*, vol. 10, no. 11, pp. 3852–3863, Nov. 2011.
[35] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.
[36] H. H. Kha, H. D. Tuan, and H. H. Nguyen, "Fast global optimal power allocation in wireless networks by local D.C. programming," *IEEE Trans. Wireless Commun.*, vol. 11, no. 2, pp. 510–515, Feb. 2012.
[37] S. Wang, F. Huang, and Z.-H. Zhou, "Fast power allocation algorithm for cognitive radio networks," *IEEE Commun. Lett.*, vol. 15, no. 8, pp. 845–847, Aug. 2011.
[38] S. Wang, M. Ge, and C. Wang, "Efficient resource allocation for cognitive radio networks with cooperative relays," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 11, pp. 2432–2441, Nov. 2013.
[39] P. Bullen, D. Mitronivic, and P. Vasic, *Means and Their Inequalities*. Dordrecht, The Netherlands: D. Reidel, 2011.
[40] C. D. Meyer, *Matrix Analysis & Applied Linear Algebra*. Philadelphia, PA, USA: SIAM, 2000.
[41] M. Fujii, J. Micic, J. E. Pecaric, and Y. Seo, "Reverse inequalities on chaotically geometric mean via specht ratio, II," *J. Inequal. Pure Appl. Math.*, vol. 4, no. 2, 2003, Art. no. 40.

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