Energy-Efficiency Maximization for D2D-Enabled UAV-Aided 5G Networks

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Abstract—Reliable and flexible emergency communication is a crucial challenge for search and rescue in the circumstance of disasters, specifically for the situation when base stations (BS) are no longer functioning. Unmanned aerial vehicle (UAV)-aided networking is becoming a prominent solution to establish emergency networks with the underlay device-to-device (D2D), which also should be energy-efficient. In this article, we study energy-efficiency (EE) maximization for interference-aware underlay D2D-enabled UAV-aided 5G systems. All the interference scenarios are taken into account while modeling the system architecture. Afterward, we formulate an objective function to optimize EE maximization, which shows the characteristic of an NP-hard nonconvex research problem. Therefore, we transform the nonconvex problem into a convex one by reformulating the constraint functions with the cubic inequality method. Several criteria are developed to satisfy the non-negativity of the reformulating constraint. This leads the problem to be solved as a convex optimization method and results in an efficient iterative resource allocation algorithm. In each iteration, the transformed problem is solved by using Lagrangian dual decomposition with a projected gradient method. In the end, we analyze the convergence behavior of the studied algorithm and also compared it with another existing algorithm through numerical simulations.

Index Terms—5G, D2D, Energy-Efficiency, Optimization, UAV.

I. INTRODUCTION

Wireless communication with unmanned aerial vehicles (UAVs) becomes a booming research topic and area of application because of their mobility and lower expense. Of late, UAV mounted base stations (BS), i.e., UAV-BS, have come into attention with effective utility as a possible solution to provide wireless connectivity in a rapid manner [1]. The terrestrial cellular network can be taken one step further by using UAV-BSs in a variety of scenarios. For example, in the case of terrestrial BSs failure, UAV-BSs can be rapidly deployed to meet the sudden demand for wireless services [1–4]. Integrating UAVs into fifth-generation (5G) (and beyond) cellular systems is a promising technology where dedicated UAVs could also be deployed as aerial communication platforms to further assist the terrestrial communications in 5G, which are referred to as UAV-aided terrestrial communications [5]. UAV-aided terrestrial communications have numerous use cases, including a device-to-device (D2D) [6] system for traffic offloading, recovery after natural disasters, emergency response, IoT, and so on. In this article, we study a scenario where a natural disaster occurs, and traditional ground BSs are destroyed and replaced by UAV-BS. Those UAV-BS revive communication with the help of a D2D-enabled system. UAV-BS replaces conventional ground BS (GBS) while natural disasters a large-scale UAV is deployed to provide wireless service to ground devices with the support of D2D-enabled links. However, in those emergencies, the energy-efficient scheme is much required for the betterment of the service.

There are quite a few works that have been published recently about energy-efficiency (EE) on UAV-aided networks. In [7], the authors attempt to minimize the UAV’s propulsion energy consumption while satisfying the throughput requirement. A variable discretization method is used to transform the problem into a discretized equivalent. In [8], the authors study joint optimization of UAV trajectory design to minimize the total energy consumption of all nodes of sensor network under the constraint that the mean square error (MSE) of estimation is below a target threshold. The authors in [9] also study the mathematical trade-offs for UAV-enabled communication platforms among three essential performance metrics: communication throughput, delay, and UAV energy consumption [9]. However, none of the works have studied for maximizing EE of an interference-aware D2D-enabled UAV-aided 5G system. One of the essential key performance indicators that originated from this trade-off is EE vs. spectral efficiency (SE) trade-off [10]. It demonstrates that EE monotonically decreases with the increasing of SE if only transmit power is applied, while EE initially increases then decreases if circuit power is considered [11]. In this article, we study optimizing EE while considering QoS (i.e., SE) constraint. Our optimization problem is an NP-hard problem. To solve this problem, we transform our problem into a convex optimization problem, which helps us to find a solution. The considered optimization problem is transformed into a convex optimization problem by redefining the constraint using the cubic inequality satisfying certain conditions to prove non-negativity. This leads the problem to be solved as a convex optimization method and results in an efficient iterative resource allocation algorithm.

The paper is organized as follows: Section II describes
the system model, which includes system architecture and reference scenario, interference scenarios, and the analytical model of the system. Section III elaborates on the studied optimization method, which brings the novelty of this work. Section IV produces an analysis of numerical results followed by the conclusion in Section V.

II. SYSTEM MODEL

In this section, we describe the system model of our investigated scenario. We divide this section into several subsections, which include system architecture, interference modeling and analytical modeling.

A. System Architecture and Reference Scenario

Fig. 1 shows the D2D-enabled UAV-aided wireless architecture. We assume that due to natural disasters, GBSs are damaged. The service providers are in the utmost urgency to establish a connection in these emergencies. Therefore due to lack of flexibility and limited fixed infrastructure, we build a link in the scenario where damaged GBS are replaced with large-scale UAV-BSs. These UAV-BSs work as moving BS to provide wireless connections to the user equipment (UE). These UEs can be cellular UE (CUE) or D2D UEs. In this paper D2D UE and CUE are only receive a control signal from the UAV-BS of the other adjacent cells. On the other hand, a CUE creates intercell interference towards adjacent BS. This interference occurrence, which is shown in Fig. 2 (a). Since the orthogonal resource allocation mechanism is used, the CUEs from the same cell do not interfere with each other. This scenario shows the intercell interference where CUE from one cell interferes with the UVA-BS of other adjacent cells.

Every CUE receives both control and data from the UAV-BS whereas D2D RX only receive a control signal from the UAV-BS. All the cellular transmissions are orthogonalized while several D2D links reutilize the same channels allocated to a CUE. Since one cellular uplink and multiple D2D links are active in this system on a given time-frequency resource and it is assumed that a CUE and its corresponding D2D RX share the same frequency band. It should be pointed out that each D2D RX can reuse the channel of multiple CUEs for different time-frequency resources. The UAV-BS contains the complete information of the instantaneous channel state information (CSI) of links to all UEs, which are assumed to experience independent block fading, and each receiver knows the fading of only its own communication link, whether it is CUE or D2D RX.

B. Interference Modeling

The scenario we described in the above section is an interference-limited multi-cell architecture. This network model creates several complex interference scenarios based on the approach described in [2]. We provide an example of those different interference scenarios in Fig. 2. The transmitted signals are categorized into two types; those are useful (desired) signals and interfering signals. Interfering signals also categorized into two categories—intracell and intercell. Moreover, a DUE consists of pair of users, which comprise (D2D TX) (the UE which acts as D2D transmitter) and (D2D RX) (the UE which receives his data from other UE instead of BS). These interference scenarios consist of both intercell and intracell interference, except Scenario 1.

Interference Scenario 1: Scenario 1 typifies an intercell interference occurrence, which is shown in Fig. 2 (a). Since the orthogonal resource allocation mechanism is used, the CUEs from the same cell do not interfere with each other. This scenario shows the intercell interference where CUE from one cell interferes with the UVA-BS of other adjacent cells.

Interference Scenario 2: In this scenario, both intracell and intercell interference is present, as shown in Fig. 2 (b). For instance, a CUE creates intercell interference towards adjacent UAV-BS and the D2D RX of those adjacent cells. On the other hand, a D2D TX generates intracell interference towards the UAV-BS of its own cell and intercell interference towards the UAV-BS of the other adjacent cells.

Interference Scenario 3: In this scenario, both intracell and intercell interference is generated by CUE and D2D TX.
simultaneously. A CUE generates intracell and intercell interference towards D2DRX and other cells’ UAV-BS, respectively, as demonstrated in Fig. 2 (c).

**Interference Scenario 4:** In this scenario, any kind of interference, be it intracell or intercell, is generated by D2D users. CUE is not responsible for creating any interference, as shown in Fig. 2 (d). D2DTX of D2D pairs from different cells create intercell interference towards UAV-BS and D2DRX of the adjacent cells, whereas intracell interference is created towards UAV-BS by the of D2DTX of the same cell.

### C. Analytical Model

We consider that in a cell $u$ a D2D pair, $d_u$ while D2DTX transmits the signal to D2DRX reuses the channel resource of CUE, $c_u$, thereby the received signal, $y^{d_u}$, at the D2DRX can be written as—

$$y^{d_u} = \sqrt{p^{d_u}} \beta h^{d_u}_c x^{d_u} + \sum_{u \neq u'} \sum_{u'=1}^{D_u} \sqrt{p^{c_u}} \rho h^{c_u}_u x^{c_u} + \sum_{u \neq u'} \sum_{u'=1}^{D_u} \sqrt{p^{c_u}} \rho h^{c_u}_u x^{c_u} + \eta^d$$

where $p^{d_u}$, $p^{c_u}$, $p^{o_u}$, and $p^{c_{u'}}$ are the transmit power for the $d_u$-th pair D2D transmitter (D2DTX), $o_u$-th pair D2DTX (i.e. transmitters from other interfering D2D pairs of the same cell $u$), the $c_u$-th CUE in the $c_u$-th channel resources of the $u$-th cell, $o_{u'}$-th pair D2DTX (i.e. transmitters from D2D pairs of the different/adjacent/interfering cells $u'$), the $c_{u'}$-th CUE of the different/adjacent/interfering cells in the $c_{u'}$-th channel resources of the $u'$-th cell, respectively. $\rho$ denotes the propagation distance, regardless of the link being cellular or D2D, and $\beta$ is the path loss exponent where $\beta \geq 4$.

$h^{d_u}_c$ is the channel gain between the $d_u$-th D2D pair of the cell $u$; $h^{c_u}_c$ is the interference channel gain between the $c_u$-th D2DTX and the $d_u$-th D2DRX of the cell $u$; $h^{d_u}_{u'}$ is the interference channel gain between the $a_{u'}$-th D2DTX and the $d_u$-th D2DRX of the cell $u$; $h^{c_u}_{c_{u'}}$ is the interference channel gain between the $c_{u'}$-th D2DTX and the $d_u$-th D2DRX of the cell $u'$. $\sigma^2$ is the AWGN with a variance of $\sigma^2$.

Afterwards, the instantaneous SINR, $\gamma^{d_u}$, at the D2DRX for a D2D user can be expressed as—

$$\gamma^{d_u} = \frac{p^{d_u} l^{-\beta} h^{d_u}_c}{I + \sigma^2} = \frac{p^{d_u} l^{-\beta} h^{d_u}_c}{I_{\text{intracell}} + I_{\text{intercell}} + \sigma^2}, \quad (2)$$

where

$$I_{\text{intracell}} = \sum_{a_{u'}=1}^{D_u} p^{o_{u'}} l^{-\beta} h^{o_{u'}}_{c_{u'}} + p^{c_{u'}} l^{-\beta} h^{c_{u'}}_{c_{u'}} \quad \text{(3)}$$

and

$$I_{\text{intercell}} = \sum_{u'=1}^{D_u} \sum_{u \neq u'} p^{o_{u'}} l^{-\beta} h^{o_{u'}}_{c_{u'}} + \sum_{u'=1}^{U} p^{c_{u'}} l^{-\beta} h^{c_{u'}}_{c_{u'}}. \quad \text{(4)}$$

Therefore, the spectral efficiency (SE), $s^{d_u}$, of the $d_u$-th pair in the $u$-th cell on the $c_u$-th reused channel can be computed as—

$$s^{d_u} = \sum_{u=1}^{U} \log_2 \left(1 + \gamma^{d_u} \right) \quad \text{(5)}$$

The total power consumption which includes transmit and circuit power is given in the following

$$p^{d_u} = \sum_{u=1}^{U} p^{c_u} + 2 * p_{\text{circuit}}. \quad \text{(6)}$$

where $p_{\text{circuit}}$ denotes the circuit power of the devices. We need to multiply the circuit power by two because of the circuit power of both D2DTX and D2DRX must be taken into account.

The utility parameter energy efficiency, $\varepsilon \varepsilon_d$, is defined as [bits/Joule/Hz], which is the ratio of total transmission rate to the total power consumption. That means,

$$\varepsilon \varepsilon_d = \frac{s^{d_u}}{p^{d_u}}. \quad \text{(7)}$$

### III. Investigated Optimization Method

#### A. Problem Formulation

We formulate the EE maximization as an optimization problem. The optimization problem is defined as

$$\max \varepsilon \varepsilon_d$$

**Subject to:**

**Constraint 1** \(s^{d_u} \leq s^{d_u}\) \(s^{d_u} \geq s^{d_u}\)

**Constraint 2** \(s^{d_u} \geq 0\)

where

$s^{d_u}$ denotes predefined minimum SE, 
$s^{d_u}$ denotes obtained SE, 
$s^{d_u}$ denotes maximum theoretical SE.

Constraint one satisfies the QoS requirement, and constraint two satisfy the nonnegativity requirement of this optimization problem. Meeting the nonnegativity criterion is of utmost importance to achieve real positive value for obtaining SE in a given period.

Our optimization problem is a combinatorial maximization problem that includes fractional function in the EE maximization problem. That means it is a complicated NP-hard problem. To solve this problem, we need to transform our problem into a convex optimization problem [12], [13].
B. Transform the optimization problem into a Convex one

In this section, we transform our NP-hard optimization problem into a solvable convex optimization problem. We redefine Constraint 1 for ensuring the convexity of the optimization problem. We adopt a method which is described in [14] for reformulating our Constraint 1 based on the nonnegativity Constraint 2. The reformulated Constraint 1 is demonstrated as a cubic inequality constraint, which assists us in finding a solution to our convex optimization problem. Our new constraint function is expressed as follows—

\[
\left( s_{d_u}^{\max} - s_{d_u} \right) \times s_{d_u} \times \left( s_{d_u} - s_{d_u}^{\min} \right) \geq 0.
\]  

(9)

From Eq. (9), we can derive two criteria which satisfy the nonnegativity condition. Those two criteria are as follows—

(i) \( s_{d_u} \in \left[ s_{d_u}^{\min}, s_{d_u}^{\max} \right], \)

(ii) \( s_{d_u} = 0. \)

Theorem 1. The reformulated constraint in Eq. (9) is achieved convexity if and only if all the criteria satisfy the nonnegativity requirement for any real nonnegative value of \( s_{d_u} \) (i.e. \( s_{d_u} \geq 0 \)).

Proof. In the following, we provide the analysis to find out which criteria satisfy the non-negativity requirement thereby providing us solution space of our problem. Since \( s_{d_u} \) is a real positive value, we assume any arbitrary value, for example, \( s_{d_u}^{\min} = 3 \) and \( s_{d_u}^{\max} = 7 \). We should keep in mind that any real positive value can be taken to prove this theorem.

**Criterion 1:** \( s_{d_u} \in \left[ s_{d_u}^{\min}, s_{d_u}^{\max} \right] \)

Closed form interval is used for this criterion, that means, the value of \( s_{d_u} \) include the endpoints of the number limit. The range of value is \( s_{d_u}^{\min} \rightarrow s_{d_u} \leq s_{d_u} \leq s_{d_u}^{\max} \). Let’s say \( s_{d_u} = 5 \). We put values of \( s_{d_u}^{\min}, s_{d_u}^{\max} \) and \( s_{d_u} \) in Eq. (9) which provides us the following equation to get a conclusion.

\[
\left( s_{d_u}^{\max} - s_{d_u} \right) \times s_{d_u} \times \left( s_{d_u} - s_{d_u}^{\min} \right) \\
= (7 - 5) \times 5 \times (5 - 3) \\
= 2 \times 5 \times 2 \\
= 20
\]

When \( s_{d_u} = s_{d_u}^{\min}, \) we obtain—

\[
\left( s_{d_u}^{\max} - s_{d_u} \right) \times s_{d_u} \times \left( s_{d_u} - s_{d_u}^{\min} \right) \\
= (7 - 3) \times 3 \times (3 - 3) \\
= 4 \times 3 \times 0 \\
= 0
\]

When \( s_{d_u} = s_{d_u}^{\max}, \) we get—

\[
\left( s_{d_u}^{\max} - s_{d_u} \right) \times s_{d_u} \times \left( s_{d_u} - s_{d_u}^{\min} \right) \\
= (7 - 7) \times 7 \times (7 - 3) \\
= 0 \times 7 \times 4 \\
= 0
\]

In all 3 circumstances, this criterion satisfies nonnegativity stipulation.

Remark: This criterion meets the nonnegativity requirement.

**Criterion 2:** \( s_{d_u} = 0 \)

If we put the values of \( s_{d_u}^{\max}, s_{d_u}^{\min} \) and \( s_{d_u} \) in Eq. (9) we get the following—

\[
\left( s_{d_u}^{\max} - s_{d_u} \right) \times s_{d_u} \times \left( s_{d_u} - s_{d_u}^{\min} \right) \\
= (7 - 0) \times 0 \times (0 - 3) \\
= 7 \times 0 \times -3 \\
= 0
\]

Remark: This criterion meets the non-negativity requirement.

From the above analysis, we can easily deduce that only all the criteria meet the non-negativity requirement. Therefore, applying those criteria, we can optimize our objective function that maximizes energy efficiency.

Moreover, when we plot the objective function of Eq. (8), we find that the EE curve is quasiconcave on SE. Fig. 3 demonstrates the EE-SE curve, which shows that EE increases with SE until some point and then decreases. In literature [11, Theorem 2], the authors proved that EE is quasiconcave on SE and is a monotonic function until circuit power is considered. This finding reconfirms the existence and the uniqueness of the globally optimal EE.

![Fig. 3: Proof of quasiconcavity (as an inverse of quasiconvexity function).](image-url)

**Theorem 2.** According to [13, Theorem 8.1, Page 204], a function \( \xi : \zeta \rightarrow \mathbb{R} \) (where \( \mathbb{R} \geq 0 \)) is quasiconcave on \( \zeta \) if and only if \( \forall \xi (\chi, \nu) \in \zeta \) and \( \forall \tau \in (0, 1) \)

\[
\xi [\tau \chi + (1 - \tau) \nu] \geq \min [\xi (\chi), \xi (\nu)]
\]

which justifies the quasiconcavity shown in Fig. 3.

Proof. For proof, please look into page 204 [13].

We can vividly find that the curve in Fig. 3 satisfies the theorem above.

The reformulated and transformed convex optimization problem can be expressed as—

\[
\max \xi e^d \\
\text{(subject to:)} \\
\left( s_{d_u}^{\max} - s_{d_u} \right) \times s_{d_u} \times \left( s_{d_u} - s_{d_u}^{\min} \right) \geq 0.
\]  

(16)
C. Iterative Energy-Efficiency Maximization Algorithm

The primary benefit of proving our optimization function is convex/concave provides us the impetus to solve our optimization problem using a convex optimization method, which is relatively easier than many other existing techniques. Using the convex optimization method (Lagrangian dual decomposition with a projected gradient), we can find a global optima for that function. Therefore, we develop one iterative EE maximization algorithm which is summarized in Algorithm 1.

Algorithm 1: Investigated Interference-Aware Energy-Efficiency Maximization Algorithm.

```
1 Input: U, C_u, D_u, t, \rho, \beta, x, \text{h}^n_{u,c}, p^d_{u,c}, \mathcal{I}, y^d_{u,c}, \gamma_d_u
2 Output: s^d_u, p^d_u, \varepsilon \varepsilon_d^t.
3 Initialize: \varepsilon_d = 10^{-5}, \varepsilon \varepsilon_d^t (t - 1)
4 while \varepsilon \varepsilon_d^t (t) - \varepsilon \varepsilon_d^t (t - 1) \leq \varepsilon_d do
5     for u = 1 : U do
6         a) Compute \mathcal{I} by using Eq. (3) and Eq. (4).
7         b) Sort \mathcal{I} in ascending order.
8         c) Compute \gamma_d_u by using Eq. (2).
9         d) Calculate \varepsilon \varepsilon_d^t (t) by using Eq. (7).
10        e) Transform objective function into a convex function by reformulating constraints into Eq. (9) which satisfies the criteria in Eq. (10).
11        f) Apply convex optimization solver (Lagrangian dual decomposition with a projected gradient method) described in [12], [13].
12     end
13 Choose the optimum solution s^d_u, p^d_u for \varepsilon \varepsilon_d^t as (s^d_u, p^d_u) = \arg \max \varepsilon \varepsilon_d^t (t).
14 Update \|D_u\|, \forall u \in U, \forall d_u \in D_u.
15 Update the iteration index as t \rightarrow t + 1.
16 Iterate until the implementation converges to the optimality.
17 (or the total number of iterations are achieved).
18 end
```

D. Complexity Analysis of the Algorithm

Channel estimation plays a significant role in terms of complexity when implementing an algorithm. Because resource optimization, which includes interference management, largely depends on channel estimation. In this article, we assume channel information is known, and each D2D pair only knows their corresponding interference information. The number of sorting operation of the algorithm helps us to find the algorithmic complexity. In this case, the quadratic function of the number of entities limit the sorting function. For example, the total number of entities is \((U \times D_u \times C_u)\) by exhaustive search, and thus the complexity is \(O(U \times D_u \times C_u)^2\), which leads to a huge number of computations. A way to bring down this complexity of the sorting operation is to sort the entities cell per cell. This method provides a similar outcome as the previous method, but with a complexity of \(O(U^2 + D_u^2 + C_u^2)\). That means the latter method demonstrates polynomial complexity, which improves its practical implementation. For instance, in a network with \(U=3, D_u=12\) and \(C_u=6\), the complexity of the former sorting technique produces \((3 \times 12 \times 6)^2 = 32,400\) number of operations, while the latter sorting method produces \((3^2 + 12^2 + 6^2) = 189\), which demonstrates a considerable decrement in terms of number of operation.

IV. NUMERICAL ANALYSIS

In this section, we provide a couple of numerical results and their analysis, which helps us to interpret the utility of our investigated algorithm. We apply the Monte-Carlo method for our simulation based on MATLAB. We follow a similar approach as in [15] to deploy UAV-BS for our paper. The decision of whether a user is D2DRX or CUE is made on the distance between transmitter and receiver. If the distance between two CUEs is less than 20 meters, users are considered as D2D users and communicate directly; otherwise, cellular users communicate via the UAV-BS. Several key simulation parameters are summarized in Table 1.

| Table I: Key Parameters |
|-------------------------|
| Parameter Name | Value |
|-----------------|-------|
| Channel bandwidth | 20 MHz |
| Noise spectral density | -174 dBm/Hz |
| Propagation loss model for cellular links | 128.1+37.6log10(\delta) [16] |
| Propagation loss model for D2D links | 148+40log10(\delta) [16] |
| Shadowing standard deviation | 8 dB |
| Number of UAV-BS (cell) | 19 |
| Total CUE per UAV-BS | 10 |
| Total D2D pairs per UAV-BS | 10, 20, 30 |
| Maximum Transmit power of UE | 23 dBm |
| Minimum SE target | 3 [(bits/s)/Hz] |

Fig. 4: Convergence of the algorithm for number of iterations vs. EE.

Fig. 4 demonstrates the convergence behavior of Algorithm 1 for EE on a different number of iterations. This result also considers a various number of D2D pairs. We find that the investigated algorithm converges efficiently to the optimum.
strategy after a reasonable amount of iterations, which might help to reduce algorithmic complexity. The higher number of D2D pairs converged early than the fewer number of D2D pairs due to space/multi-user diversity and opportunistic selection of the channel. Moreover, D2D users receive less transmission power due to the short transmission distance between transmitter and receiver, which also helps to reduce the severe interference compare to cellular users.

Fig. 5 compares the studied EE maximization algorithm with the conventional margin adaptive (MA) [17] algorithm. Both algorithms perform based on the QoS constraint requirements. However, conventional MA only focuses on transmit power minimization. In Fig 5, both methods show quasiconcavity of EE on SE, as proved in the previous section, thanks to the inclusion of circuit power. Our approach provides better EE than the conventional MA since MA’s goal is not to maximize EE but to minimize the total transmit power subject to minimum QoS constraints. Therefore, MA receives only its minimum required data. Another important feature we can observe from this context (at high QoS requirements), and the solutions to both problems tend to become similar. It proves the efficacy of the investigated method, which optimizes EE for low QoS requirements. The reason for that behavior is a no-brainer as QoS demands are increased, the number of feasible solutions (that acts in accordance with problem constraints) to both optimization problems is considerably reduced. Therefore, the optimization objective function plays a less significant role in this context (at high QoS requirements), and the solutions to both problems tend to become similar. It proves the efficacy of the investigated method, which optimizes EE for low QoS requirements compare to the MA method.

V. CONCLUSIONS

In this paper, we study an energy-efficiency maximization algorithm for D2D-enabled UAV-aided 5G networks. We consider and design multiple scenarios of interference which occurs in a realistic environment. Our optimization problem is a nonconvex one; therefore, we reformulated the constraints of our optimization problem by using the cubic inequality method. It helps us to redesign our optimization problem, which can be solvable by applying the convex optimization method. We have shown that our method outperforms the conventional MA algorithm while considering QoS demand as a constraint. This work leads us to find an iterative EE optimization scheme for the UAV-aided networks for 5G and beyond where energy is a scarce commodity.

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REFERENCES

[1] M. Alzenad, A. El-Keyi, F. Lagum, and H. Yankomeroglu, “3-D Placement of an Unmanned Aerial Vehicle Base Station (UAV-BS) for Energy-Efficient Maximal Coverage,” IEEE Wireless Communications Letters, vol. 6, no. 4, pp. 434–437, Aug 2017.
[2] Z. Zhou, M. Dong, K. Ota, G. Wang, and L. T. Yang, “Energy-Efficient Resource Allocation for D2D Communications Underlaying Cloud-RAN-Based LTE-A Networks,” IEEE Internet of Things Journal, vol. 3, no. 3, pp. 428–438, June 2016.
[3] I. Bor-Yaliniz and H. Yankomeroglu, “The New Frontier in RAN Hetereogeneity: Multi-Tier Drone-Cells,” IEEE Communications Magazine, vol. 54, no. 11, pp. 48–55, November 2016.
[4] Y. Zeng, R. Zhang, and T. J. Lim, “Wireless Communications with Unmanned Aerial Vehicles: Opportunities and Challenges,” IEEE Communications Magazine, vol. 54, no. 5, pp. 36–42, May 2016.
[5] N. Zhao, W. Lu, M. Sheng, Y. Chen, J. Tang, F. R. Yu, and K. Wong, “UAV-Assisted Emergency Networks in Disasters,” IEEE Wireless Communications, vol. 26, no. 1, pp. 45–51, February 2019.
[6] K. M. S. Huq, S. Mumtaz, J. Rodriguez, P. Marques, B. Okyere, and V. Frascolla, “Enhanced C-RAN Using D2D Network,” IEEE Communications Magazine, vol. 55, no. 3, pp. 100–107, March 2017.
[7] F. Dong, L. Li, Z. Lu, Q. Pan, and W. Zheng, “Energy-Efficiency for Fixed-Wing UAV-Enabled Data Collection and Forwarding,” in 2019 IEEE International Conference on Communications Workshops (ICC Workshops), May 2019, pp. 1–6.
[8] C. Zhan and G. Yao, “Energy Efficient Estimation in Wireless Sensor Network With Unmanned Aerial Vehicle,” IEEE Access, vol. 7, pp. 63 519–63 530, 2019.
[9] Q. Wu, L. Liu, and R. Zhang, “Fundamental Trade-offs in Communication and Trajectory Design for UAV-Enabled Wireless Network,” IEEE Wireless Communications, vol. 26, no. 1, pp. 36–44, February 2019.
[10] Y. Chen, S. Zhang, S. Xu, and G. Y. Li, “Fundamental trade-offs on green wireless networks,” IEEE Communications Magazine, vol. 49, no. 6, pp. 30–37, June 2011.
[11] C. Xiong, G. Y. Li, S. Zhang, Y. Chen, and S. Xu, “Energy- and Spectral-Efficiency Tradeoff in Downlink OFDMA Networks,” IEEE Transactions on Wireless Communications, vol. 10, no. 11, pp. 3874–3886, November 2011.
[12] S. Boyd and L. Vandenberghe, Convex Optimization. Cambridge University Press, Mar. 2004.
[13] R. K. Sundaram, A First Course in Optimization Theory. Cambridge University Press, Jun. 1996.
[14] C. Li, H. Xiong, J. Zou, and Z. He, “Joint Source and Flow Optimization for Scalable Video Multirate Multicast Over Hybrid Wired/Wireless Coded Networks,” IEEE Transactions on Circuits and Systems for Video Technology, vol. 21, no. 5, pp. 550–564, May 2011.
[15] L. Liu, S. Zhang, and R. Zhang, “CoMP in the Sky: UAV Placement and Movement Optimization for Multi-User Communications,” IEEE Transactions on Communications, vol. 67, no. 8, pp. 5645–5658, Aug 2019.
[16] L. Xu, G. Yu, and R. Yin, “Joint Power Allocation and Reuse Partner Selection for Device-to-Device Communications,” in 2015 IEEE 81st Vehicular Technology Conference (VTC Spring), May 2015, pp. 1–5.
[17] M. Moretti and A. I. Perez-Neira, “Efficient Margin Adaptive Scheduling for MIMO-OFDMA Systems,” IEEE Transactions on Wireless Communications, vol. 12, no. 1, pp. 278–287, January 2013.