Energy-Efficient UAV-Relaying 5G/6G Spectrum Sharing Networks: Interference Coordination With Power Management and Trajectory Design

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ABSTRACT As massive ground users access wireless networks with limited available spectrum, coexisting users that share the same spectrum band severely interfere with each other. Moreover, communication pairs without direct communication links may suffer from severe outage issues. In this paper, unmanned aerial vehicle (UAV) relaying-assisted interference coordination is proposed to enhance data transmission reliability by 1) relaying transmission, and 2) alleviating mutual interference among ground users. To efficiently utilize confined UAV energy such that the UAV relaying service life can be significantly prolonged, the full-duplex (FD) technique is exploited. An exact energy efficiency (EE) maximization problem is formulated, which jointly optimizes throughput and UAV energy consumption. Different from the traditional offline method, online power management and trajectory designs are performed under the information causality and rate constraints. Considering that power management and trajectory are coupled, we design a block coordinate descent method to efficiently solve the optimization problem. Numerical results demonstrate that the proposed scheme outperforms existing schemes, and the EE is about 30% and 46% higher than those of the genetic algorithm and half-duplex scheme, respectively. Moreover, impacts of different positions and the maximum power of ground users on the EE have been demonstrated.

INDEX TERMS Energy efficiency (EE), full-duplex relaying, mutual interference coordination, unmanned aerial vehicle (UAV) relay.

I. INTRODUCTION

UNMANNED aerial vehicles (UAVs) have been widely used in assisting wireless networks [1] due to their advantages of low cost, flexible deployment, and high mobility, especially in communication scenarios that are difficult for human beings to reach (e.g., fire and earthquake affected area) [2], [3]. Academia and industry have put considerable efforts in integrating UAVs-enabled communications into the forthcoming fifth/sixth-generation (5G/6G) networks [4], [5], such as cellular offloading for the overloaded
base stations (BSs), power charging and data collection for device-to-device (D2D) scenarios [6]. For example, in [7], the authors investigated a mobile UAV-relaying Internet of Things (IoT) scenario for sensor data collection. The authors in [8] researched UAV relay systems for vehicular and hoc network. Therein, a relaying system was designed for environmental monitoring and agricultural applications. In addition, AT&T designed UAV-assisted wireless transmissions on its 5G wireless networks to enhance large-scale wireless communication [9]. With the development of intelligent reflective surfaces, the performance of UAV-aided air-ground networks can be enhanced [10].

Recent works have investigated UAV as a mobile data collector paradigm in primarily four directions: 1) jointly optimize UAV transmission power and trajectory to maximize the network throughput [6], [11], [12]; 2) jointly schedule ground users’ wake-up mode and UAV’s trajectory [13]; 3) minimize either UAV energy consumption or the ground user power consumption; 4) jointly optimize the UAV trajectory and time scheduling [2]. It is worth noting that the service life of UAV is limited by its practical size, weight, and on-board battery capacity. UAVs on the market today, e.g., DJI and Yuneec, generally have flight durations of around 5-30 minutes [14]. Hence, achieving more data transmission per unit of power (i.e., maximizing energy efficiency (EE)) is a critical issue in UAV integrated networks [15]. However, in addition to the severe path losses and physical blockage, transceivers may also suffer from strong interference from neighbouring infrastructures, including ground user equipment (UE), neighbouring BSs, and other UAVs. What’s worse for a UAV relay, it may suffer two-fold interference, i.e., in the first and second hops [16]. On the other hand, compared with terrestrial communication systems, UAV-assisted wireless systems also have superior ground nodes (GNs) channel link quality resulting in strong interference to other users. Thus, interference coordination between UAV relays and other neighbouring nodes is one of the key challenges in UAV-relaying communications. Motivated by the above-mentioned issues, this paper focuses on maximizing the EE of UAV-relaying 5G spectrum sharing wireless networks. The mutual interference between UAV and ground nodes is mitigated by carefully designing the UAV’s trajectory and power coordination among all transmitters.

A. RELATED WORK
Given the recent progress of the self-interference (SI) cancellation technique [17], the full-duplex relaying (FDR) networks have outperformed those of the half-duplex (HD) scheme in most communication scenarios [18], [19], [20], [21], given energy-constrained nodes. The full-duplex (FD) UAV-relaying scheme is exploited with the prospect of improving EE [22], [23]. Current state-of-the-art on UAV relays focus on the half-duplex relaying (HDR) systems [24], [25], [26]. The authors in [24] formulated a joint transmission power and trajectory optimization problem for UAVs in HD two-way multi-hop UAV relaying network, which achieved significant throughput gains. However, HD has an inherent delay compared to FD which needs to take more energy [27]. There are some studies on the FD UAV-relaying assisted with the GNs communications. The authors in [22] proposed UAV acting as a relay and forwards information exchange between two GNs. Nevertheless, the UAV only flew in a straight line and could not adjust its transmission power in [22]. The potential of FDR-UAV in improving EE needs to be further explored, especially for scenarios with multiple GNs, but limited available spectrum.

Though UAV-assisted networks with GNs communications have been actively studied [15], [26], [28], few works have studied scenarios where multiple GNs share a frequency and interfere with each other. The authors in [15] studied energy efficient UAV communication with a GN by optimizing the UAV’s trajectory, which considered UAV propulsion energy consumption, and derived a theoretical model on the consumption. Similarly, the authors in [28] focused on the EE maximization problem in UAV-relaying networks with a single ground user, in which the HD mode was exploited at UAV relay. In [26], the authors studied optimal UAV trajectory, and design energy efficient UAV communication, which considered a single GN in the system. Unfortunately, the aforementioned works mainly focused on classic communication scenarios without mutual interference, thus not feasible in multi-user scenarios where spectrum resources are scarce, and thus spectrum sharing needs to be utilized [29]. However, this introduces mutual interference between the users. Different from [15], [26], [28] that investigated single ground user scenarios, [30] studied UAV-assisted networks with multiple communicating ground pairs. Static UAV-relay positions and relay assignment are jointly optimized to maximize the network throughput.

Recently papers have jointly optimized transmission power and trajectory to achieve various objectives, such as network throughput maximization [31], [32], [33], transmission reliability (e.g., bit error rate (BER), outage probability [34], [35], and secrecy rate maximization [2], [36]). Paper [31], is the first work that proposed a general mathematical framework to jointly optimize the UAV trajectory and transmission power of mobile UAV relays, aimed at maximizing data transmission rate. The classic three-node communication system that consists of fixed source-destination pair and assisted by a mobile relay was investigated. Instead of focusing on capacity metric, a few works focused on the reliability. In [32], [33], the authors adopted the convex approximation method to jointly optimize the trajectory and power of UAVs to maximize network throughput. By using realistic UAV channel models, the authors in [34] investigated the optimum UAV altitude as a relaying station to minimize BER and outage probability. Numerical results illustrated that decode-and-forward (DF) outperforms amplify-and-forward (AF). The authors in [35] considered HD uplink UAV relay network with a UAV, a BS, and a mobile device, in which UAV worked in HD and AF mode.
The outage probability was minimized through joint trajectory design and power control. The authors in [37] studied the impacts of parameters on reliability performance to reveal useful insights on the practical design of cellular-connected UAV swarm communication. However, all the aforementioned works ignored UAV propulsion energy consumption. In practice, during signal transmission, the propulsion energy consumption of UAV affects the transmission efficiency. Thus, it is important to improve the number of bits transmitted per joule, i.e., the EE [15], [38]. Additionally, the authors in [39], [40] optimized the deployment of UAV locations or transmission power to achieve energy efficient communication, but with a simplified formulation of energy cost.

In addition, GN may be movable and its transmission power may change from time to time. Therefore, a potentially malicious external agent that dynamically exerts jamming on the UAV. As has been studied in most published works, the off-line trajectory design that plans the entire flight path at one time will still face many challenges. For example, in dynamic environment, UAV offline optimal strategy is difficult to avoid jamming, while in the online mode, UAV trajectory can be dynamically adjusted when wireless transmission environment changes [41]. Moreover, online mode needs to optimize the EE of the current time interval and at the same time ensure that UAVs can reach the destination. However, there are few works focusing on the online UAV trajectory optimization. The authors in [42] designed an efficient spectrum sharing technology for UAV and D2D communications by optimizing transmission power and trajectory. But it considered the online decision mode and neglected UAV’s flight energy consumption. The authors in [43] proposed an iterative solution for obtaining optimal UAV trajectory in online mode, which took into account the same propulsion energy consumption as in [15]. However, the optimization of transmission power was neglected in this paper.

B. CONTRIBUTIONS AND ORGANIZATION

In summary, the majority of prior works that focused on the UAV-assisted wireless networks took either network throughput [24], [31], secrecy rate [2], or GN energy consumption [13] as a metric, while they either ignored the UAV propulsion energy consumption or over-simplified the energy consumption model. Moreover, the resource allocation strategies proposed in [15], [26], [28] are inappropriate to networks with coexisting ground users that share the same spectrum band since 1) most UAV-relay related works considered that there is only one source-destination pair, and ignored UAV-assisted user interference coordination problem; 2) FD technique of UAV-relay has not been fully investigated, and 3) offline mode is difficult to adapt to complex and changeable scenarios.

To satisfy the increased EE requirements of future spectrum sharing wireless networks, we investigate the UAV-integrated 5G wireless networks, where FD relaying and mitigate mutual interference coordination techniques are utilized. Different from existing works, EE maximization problems in FD UAV-relaying networks in online mode are studied. Specifically, the main contributions of our work are listed as follows:

1. For UAV-relay networks, the FD technique is deployed and mutual interference is coordinated for scenarios with multiple ground users, aiming at improving the EE. Additionally, an online optimization method is proposed to maximize EE and ensure that UAVs can adapt to a dynamic environment and complete flight missions. To the best of our knowledge, this is the first work on EE maximization for UAV relays that integrates FD technique and interference mitigation in online mode.

2. An EE optimization problem is formulated under the information causality and rate bound constraints, which focuses on the joint optimization of UAV trajectory and transmission power of all transmitters. To address complex non-convex optimization problem with highly coupled variables, the non-convex fractional programming problem is first converted into its subtractive form, and then further decomposed into two sub-problems by utilizing block coordinate decent and successive convex optimization methods.

3. Simulation results show that our scheme outperforms the existing schemes in convergence speed (and whatever else), which suggests the superiority of our method in this scenario. Moreover, the information causality and rate bound constraints are both satisfied. In addition, impacts of the following parameters, including 1) geographical position distributions of ground transceivers, and 2) the maximum power of ground nodes are investigated, which has a great impact on the optimal trajectory and power.

The rest of this paper is organized as follows. In Section II, the system model is introduced. In Section III, the EE maximization problem is formulated, considering the joint optimization of UAV trajectory and power control of all nodes. The primal complex optimization problem is decomposed into two sub-problems, i.e., trajectory optimization and power optimization, that are further approximated by their convex-forms in Sections IV and V, respectively. Based on that, the joint optimization problem is provided in Section VI. Simulation results are presented in Section VII, and the paper is concluded in Section VIII.

Notations: The notations are listed in Table 1.

II. SYSTEM MODEL

As shown in Fig. 1, a general 5G spectrum sharing wireless network is considered, where there are two co-existing transceiver pairs, i.e., $T_s - T_d$ and $T_g - T_r$. Assume that $T_s$ intends to transmit its signal to its destination $T_d$; meanwhile, $T_g$ has messages to be transmitted to $T_r$. However, there exists no direct link between users within the same pair.
Table 1. Notations.

| Notation | Description |
|----------|-------------|
| $m \in \mathbb{N}^+$ | Time interval index |
| $i \in \{T_s, T_g, T_r, T_e\}$ | Distance between UAV-T$_i$ at the beginning of the $m$th time interval |
| $(x_i, y_i)$ | The coordinate of the node $i$, $i \in \{T_s, T_g, T_r, T_e\}$ |
| $(x_m, y_m, H)$ | UAV coordinates at the beginning of the $m$th time interval |
| $d_{g,e}$ | Distance between $T_g$ and $T_e$ |
| $d_{s,g}$ | Distance between $T_s$ and $T_g$ |
| $D_{s,m}$ | $x_{m} - x_{m-1}$ |
| $D_{g,m}$ | $y_{m} - y_{m-1}$ |
| $D_{D,m}$ | $\sqrt{(x_{m} - x_{m-1})^2 + (y_{m} - y_{m-1})^2}$ |
| $P_m$ | The set of $P_{s,m}, P_{g,m}, P_{r,m} (\forall m)$ |
| $q_m$ | The optimal BE in the $m$th time interval |

(Without loss of generality, we take $T_s$ - $T_d$ pair as an example for analysis). Furthermore, due to limited electromagnetic spectrum resources, the above two pairs have to communicate simultaneously at the same spectrum band. Hence, the pairs will experience mutual interference between them.\(^1\)

A rotary-wing UAV flies within a specified aerial area and is deployed to assist relaying $T_s$ - $T_d$ transmission. Particularly, to fully exploit the relaying capacity and enhance the data transmission EE, FDR technique is applied to the UAV that is equipped with two antennas, one for receiving and the other for transmitting. The UAV is also equipped with global positioning system (GPS) and the use of GPS will enable the UAV to complete their mission by following the trajectory and hover in need [44]. We assume that the UAV flies at a fixed altitude $H$ within a finite time duration $T$. The overall UAV trajectory is split into $M$ segments in terms of time intervals. To be specific, the duration of each segment is the same and equal to $T/M$; however, due to the flight speed of UAV in each segment is not identical and the time interval is same in each segment, the distance of the $m$th segment ($m = 1, 2, \ldots, M$), denoted by $DD_m$ is not identical.

A. T$_s$-UAV DATA TRANSMISSION

In the $m$th time interval, the signal received at UAV can be formulated as

$$y_{r,m} = \sqrt{P_{s,m}}d_{s,m}^{-2}S'_{s,m} + \sqrt{P_{g,m}}d_{g,m}^{-2}S'_{g,m}$$

Transmitted signal from $T_s$ 

Interference from $T_g$ 

$$+ \sqrt{P_{r,m}}h_{rr}[k_0S'_{r,m}] + n_1, \ m = 1, 2 \ldots M - 1.$$  \hspace{1cm} (1)

UAV SI

where the first term is the signal sent from $T_s$; the second and third terms are interference from $T_g$ and SI, respectively; $n_1$\(^1\)

1. Note that our model can be readily extended to scenarios with multiple co-existing pairs. Here we only take one co-existing pair as an example to illustrate the system design. For easy notations and maintenance of generality, we assume that $T_s$ - $T_d$ and $T_g$ - $T_e$ share identical frequency band in each time interval. when $T_s$ transmits information to $T_e$, mutual interference will be caused between $T_g$ and the UAV’s receiving antenna, $T_s$ and $T_g$, Similarly, mutual interference will be caused between $T_s$ and $T_e$, the UAV’s transmitting antenna and $T_e$.

is the additive white Gaussian noise (AWGN) at UAV with mean power $\sigma_r^2$; $P_{s,m}, P_{g,m}$, and $P_{r,m}$ denote transmission power of $T_s$, $T_g$, and UAV at the $m$th time interval, respectively; $k_0$ and $h_{rr}$ are the SI cancellation factor and channel power gains of the UAV, respectively; $S'_{s,m}, S'_{g,m}$ and $S'_{r,m}$ are the signal transmitted by $T_s$, $T_g$, and UAV at the $m$th time interval, respectively.

Since the UAV relay has processing delays, the UAV cannot immediately decoded and forward the received signal. Here we assume that there is a processing delay of $\tau$ time intervals and DF mode is applied. In the case that the UAV can successfully decode the signal, the forwarded signal from UAV in the $m$th time interval is $S'_{l,m-\tau}$. That is, $S'_{l,m} = S'_{l,m-\tau}$.

It can be obtained that $T_s$-UAV data transmission capacity in the $m$th time interval is

$$SINR_{s,m} = \frac{P_{s,m}d_{s,m}^{-2}}{P_{g,m}d_{g,m}^{-2} + k_0P_{r,m}|h_{rr}|^2 + \sigma_r^2}.$$  \hspace{1cm} (2)

Then, $T_s$-UAV channel capacity is given by

$$C_{s,m} = \log_2(1 + SINR_{s,m}).$$  \hspace{1cm} (3)

B. UAV FORWARDS SIGNALS TO T$_d$

With interference from $T_g$, the signal received at $T_d$ is

$$y_{f,d} = \sqrt{P_{r,m}}d_{d,m}^{-2}S'_{l,m-\tau} + \sqrt{P_{g,m}}d_{g,2}^{-2}S'_{g,m} + n_2.$$  \hspace{1cm} (4)

where $m = 1, 2, \ldots, M - 1$,

$$S'_{g,m} = \text{the transmitted signal from } T_g; \ n_2 \text{ is the AWGN noise at } T_d \text{ with mean power } \sigma_g^2.$$  \hspace{1cm} (5)

It can be obtained that the SINR at $T_d$ in the $m$th time interval is

$$SINR_{d,m} = \frac{P_{r,m}d_{d,m}^{-2}}{P_{g,m}d_{g,m}^{-2} + \sigma_g^2}.$$  \hspace{1cm} (6)

Correspondingly, the channel capacity of UAV-$T_d$ link is

$$C_{d,m} = \log_2(1 + SINR_{d,m}).$$  \hspace{1cm} (7)
C. $T_G - T_E$ DATA TRANSMISSION

With interference from UAV-$T_d$ transmission and $T_j$-UAV transmission, the signal received at $T_e$ is

$$y_{T_e,m} = \sqrt{P_{g,m}d_{g,e}^{-2}S_{g,m}^2} + \sqrt{P_{r,m}d_{r,e,m}^{-2}S_{r,m}^2 - \Sigma_n} + 1, \quad m = 1, 2, \ldots, M - 1,$$

where $d_{s,e}$ is $T_s - T_e$ distance, $n_e$ is the AWGN noise at $T_e$ with mean power $\sigma^2$.

$T_e - T_d$ data transmission channel capacity in the $m$th time interval is calculated as

$$C_{g,m} = B\log_2 \left( 1 + \frac{P_{g,m}d_{g,e}^{-2}}{P_{r,m}d_{r,e,m}^{-2} + P_{s,m}d_{s,e}^{-2} + \sigma^2} \right).$$

III. PROBLEM FORMULATION

This study aims at mitigating the mutual interference among communication pairs to improve EE by optimizing: 1) the data transmission power at $T_s$, $T_g$, and the UAV; and 2) the trajectory of the UAV. Hereinafter, the objective function, namely EE, and constraints are respectively formulated.

A. EE FORMULATION

EE is defined as the sum capacity divided by the total power consumption. In the $m$th time interval, let $y_m$ be the data transmitting rate from $T_s$ to $T_j$ with the assistance of the UAV relay. Thus, $y_m$ can be defined as

$$y_m = \begin{cases} 0, & m = 1, 2, \ldots, \tau - 1, \\ \min\{C_{s,m}, C_{d,m}\}, & m = \tau, \tau + 1, \ldots, M - 1. \end{cases}$$

Then, the sum capacity of two-user pairs in the $m$th time interval is $y_m + C_{g,m}$.

The overall power consumption consists of UAV propulsion power consumption and communication power consumption. Only the former one is emphasized, since it is much higher than the latter, as concluded in [45]. The UAV power model in [45] is adopted. The flight distance in the $m$th time interval can be easily extracted as

$$DD_m = \sqrt{(s_{m} - x_{m-1})^2 + (y_{m} - y_{m-1})^2},$$

where $x_m$ and $y_m$ are UAV coordinates at the beginning of the $m$th time interval. Further, the flight speed in the $m$th time interval is given as $v_m = DD_m / T_m$.

Let $P_0$ and $P_1$ respectively represent the blade profile power and induced power, which can be formulated as

$$P_0 = \frac{\varepsilon \rho s \Omega^3 R_0^3}{8}, \quad P_1 = (1 + k_h) \frac{W^{3/2}}{2 \rho A},$$

where $s$ and $R_0$ are rotor solidity and rotor radius (measured in meter), respectively; $\varepsilon$ is the profile drag coefficient; $\Omega$ is the blade angular velocity in radians; $k_h$ is the incremental correction factor to induced power; $W$ is the aircraft weight in Newton; $\rho$ is the air density; and $A$ is the rotor disc area.

Then, the overall power consumption [45] in the $m$th time interval is

$$P_{t_{ot,m}} = \left[ P_0 \left( 1 + \frac{3DD_m^2}{U_{tip}^2 \cdot T^2 / M^2} \right) + P_1 \frac{\rho \Omega}{2} \frac{DD_m^2}{T_m^3} \right].$$

where $U_{tip}$ is the tip speed of the rotor in hovering state; $f_0$ is the fuselage drag ratio.

Then the objective function in the $m$th time interval, denoted by $\eta_{EE,m}$, is given as

$$\eta_{EE,m} = \frac{y_m + C_{g,m}}{P_{t_{ot,m}}}, m = 1, 2, \ldots, M - 1.$$  

Next, constraints on the data transmission rate, information causality, and UAV flight behaviour are formulated, respectively.

B. CONSTRAINTS FORMULATION

1) CONSTRAINTS ON THE DATA TRANSMISSION RATE

To ensure the transmission delay, it is required that data transmission rate for both $T_s$ and $T_g$ be larger than their respective thresholds, denoted by $C_{2,th}$ and $C_{3,th}$. That is,

$$C_{d,m} \geq C_{d,th}, \quad m = \tau, \tau + 1, \ldots, M - 1,$$

$$C_{g,m} \geq C_{g,th}, \quad m = 1, 2, \ldots, M - 1.$$  

2) CONSTRAINTS ON THE INFORMATION CAUSALITY

The UAV relay has to satisfy the information causality. That is, the number of bits forwarded to $T_d$ cannot exceed the number of bits received by $T_s$. Hence,

$$C_{s,0} + \sum_{m=1}^{\tau} C_{s,m} \geq \sum_{m=\tau}^{M-1} C_{d,m}, \quad \forall i \in N^+.$$  

3) CONSTRAINTS ON THE UAV FLIGHT BEHAVIOUR

In practice, the departure position ($x_s, y_s, H$) and the destination position ($x_d, y_d, H$) of the UAV flight are pre-determined. That is,

$$x_0 = x_s, y_0 = y_s, x_{M-1} = x_d, y_{M-1} = y_d.$$  

Additionally, the UAV flight speed is upper bounded by its maximum value, $V_{max}$. It is required that

$$DD_m \leq V_{max} \frac{T}{M}, \quad \forall m, m = 1, 2, \ldots, M - 1,$$

where $DD_m$ in (11) satisfies

$$DD_m^2 = D_{x,m}^2 + D_{y,m}^2,$$

and $D_{x,m}$, $D_{y,m}$ are respectively defined as

$$D_{x,m} = x_m - x_{m-1}, \quad D_{y,m} = y_m - y_{m-1}.$$
C. PRIMAL PROBLEM FORMULATION

According to (10), \( C_{s,m} \geq \gamma_m \) and \( C_{d,m} \geq \gamma_m \) should be satisfied. Hence, the online optimization problem is

\[
\textbf{P1: } \max_{P_{m},x_{m},y_{m}} \frac{\gamma_m + C_{g,m}}{P_{\text{tot},m}}, \quad m = 1, 2, \ldots, M, \quad (22)
\]

\[
\text{s.t. } \quad (15) \sim (21), \quad \text{(23)}\]

\[
C_{s,m} \geq \gamma_m, \quad m = 1, 2, \ldots, M - 1, \quad (23)
\]

\[
C_{d,m} \geq \gamma_m, \quad m = 1, 2, \ldots, M - 1, \quad (24)
\]

\[
P_{m} \geq 0, \quad x_{m} \geq 0, \quad y_{m} \geq 0, \quad (25)
\]

where \( P_{m} \) is the set of \( P_{s,m}, P_{g,m}, P_{r,m} \) (\( \forall m \)).

Note that \( \textbf{P1} \) focuses on optimizing EE in an online mode, that is, EE in each time interval is optimized without violating the data transmission rates in each time interval.

D. PRIMAL PROBLEM TRANSFORMATION

The fractional form of the objective function makes it complicated to analyze. Hereinafter, the Dinkelbach’s method [46] is applied to transform the fractional objective function into its subtractive form. The following proposition is provided.

**Proposition 1:** The joint optimization of power allocation and UAV trajectory can achieve the maximum EE

\[
q^{*}_m = \max \{\eta_{EE,m}\}, \quad m = 1, 2, \ldots, M - 1,
\]

if and only if

\[
V(q^{*}_m, P^{*}_m, x^{*}_m, y^{*}_m) = \max_{q_m \geq 0} \{\gamma_m + C_{g,m} - q_m P_{\text{tot},m} = 0\},
\]

\[
m = 1, 2, \ldots, M - 1,
\]

where \( q^{*}_m \) is the maximum EE, \( P^{*}_m \) is the set of optimum solutions of \( P_{s,m}, P_{g,m}, P_{r,m} \) (\( \forall m \)), while \( x^{*}_m, y^{*}_m \) are the optimum location solutions of the \( m \)th time interval.

Proposition 1 indicates that \( \textbf{P1} \) can be solved equivalently if the maximum value of the objective function’s subtractive form equals to zero, i.e.,

\[
\gamma_m + C_{g,m} - q_m P_{\text{tot},m} = 0, \quad m = 1, 2, \ldots, M - 1. \quad (28)
\]

Motivated by Proposition 1, we will focus on solving the equivalent optimization problem formulated below:

\[
\textbf{P2: } \max \quad V(P_{m}, x_{m}, y_{m}, \gamma_m) = \gamma_m + C_{g,m} - q_m P_{\text{tot},m}, \quad m = 1, 2, \ldots, M - 1,
\]

\[
\text{s.t. } \quad (15) \sim (25). \quad (29)
\]

Note that \( q^{*}_m, P^{*}_m, x^{*}_m, y^{*}_m, \gamma^{*}_m \) have to satisfy

\[
\max \{V(q^{*}_m, P^{*}_m, x^{*}_m, y^{*}_m, \gamma^{*}_m) = 0, \quad (30)
\]

or equivalently

\[
\min \quad V' = -V = 0. \quad (31)
\]

That is, \( \textbf{P2} \) can be further equivalently transformed into \( \textbf{P3} \) as shown below:

\[
\textbf{P3: } \min \quad V'(P_{m}, x_{m}, y_{m}, \gamma_m) = q_m P_{\text{tot},m} - \gamma_m
\]

\[
-C_{g,m} m = 1, 2, \ldots, M - 1,
\]

\[
\text{s.t. } \quad (15) \sim (25). \quad (32)
\]

According to (27) and (31), \( \min \{V(q^{*}_m, P^{*}_m, x^{*}_m, y^{*}_m, \gamma^{*}_m) \} = 0 \) must be held, which provides an indicator for verifying the optimality of the solutions. The search for \( q^{*}_m, P^{*}_m, x^{*}_m, y^{*}_m, \gamma^{*}_m \) ends when \( |V'| \leq \delta \), where \( \delta \) is the preset tolerance. \( q_m \) is iteratively updated, and the detailed updating rule can be found in [46].

Note that power allocation and UAV trajectory are coupled, making it difficult to solve \( \textbf{P3} \). Thus, the block coordinate descent (BCD) method is used to solve \( \textbf{P3} \) by decomposing it into sub-problems of trajectory and power optimization, respectively.

IV. TRAJECTORY OPTIMIZATION PROBLEM TRANSFORMATION

Based on the aforementioned analysis, given the transmission power at different nodes, the trajectory optimization problem can be formulated as below,

\[
\textbf{P4: } \min \quad V_{r,m} = q_m P_{\text{tot},m} - \gamma_m - C_{g,m}, \quad m = 1, 2, \ldots, M - 1,
\]

\[
\text{s.t. } \quad (15) \sim (25). \quad (34)
\]

which is a non-convex optimization problem due to the existence of non-convex term \( DD_m \) in \( P_{\text{tot},m}, C_{g,m} \) in the objective function, and \( C_{s,m} \) and \( C_{d,m} \) in the constraints. Next, the trajectory optimization problem is transformed and approximated by its convex form.

A. DISTANCE CONSTRAINTS TRANSFORMATION

The existence of \( d_{s,m}^2 \) \( (i \in \{T_s, T_d, T_g, T_e\}) \) makes the objective function and constraints non-convex and mathematically intractable. Alternatively, four new variables are introduced in the order that the optimization problem can be analyzed and converted into their convex forms mathematically. Specifically, they are defined as below:

\[
S_{s,m} = d_{s,m}^2 = \frac{1}{(x_m - x_s)^2 + (y_m - y_s)^2 + H^2},
\]

\[
S_{d,m} = d_{d,m}^2 = \frac{1}{(x_m - x_d)^2 + (y_m - y_d)^2 + H^2},
\]

\[
\min_{T_{r,m}} q_m P_{\text{tot},m} - \gamma_m - \text{Blog}_2 \left( P_{g,m} S_{g,m} + S_{s,m} + \alpha_{1,m} \right) + \text{Blog}_2 \left( P_{r,m} S_{r,m} + \alpha_{1,m} \right) + \frac{B}{P_{r,m} S_{r,m} + \alpha_{1,m}} \left( S_{r,m} - S_{r,0} \right) \quad (33)
\]
= \frac{1}{H^2}, j \in \{g, e\},
\] when \( m = 1, 2, \ldots, M - 1 \).

Clearly, (35) \sim (37) are not in convex forms. However, they can be equivalently relaxed as below:

\[
\begin{align*}
\frac{1}{S_{s,m}} & \geq (x_m - x_s)^2 + (y_m - y_s)^2 + H^2, \\
\frac{1}{S_{d,m}} & \geq (x_m - x_d)^2 + (y_m - y_d)^2 + H^2, \\
\frac{1}{S_{j,m}} & \leq (x_m - x_j)^2 + (y_m - y_j)^2 + H^2,
\end{align*}
\]

(38)\sim (40)

Since decreasing \( 1/S_{s,m} \) and \( 1/S_{d,m} \) leads to the increase of the objective value, while increasing \( 1/S_{j,m} \), \( j \in \{g, e\} \) also leads to an increasing objective value, the above four variables in (38)\sim (40) are driven to take their bounds in the optimization. In other words, though being relaxed into inequality constraints, all constraints in (38)\sim (40) will be met with equality.

By further applying the first-order Taylor expansion, constraints in (38)\sim (40) are rewritten as

\[
\begin{align*}
x_{r,m}^2 + y_{r,m}^2 + H^2 - \left[ \frac{1}{S_{s,m}} - \frac{1}{S_{s,m}^{(0)}} (S_{s,m} - S_{s,m}^{(0)}) \right] & \leq 0, \\
x_{d,m}^2 + y_{d,m}^2 + H^2 - \left[ \frac{1}{S_{d,m}} - \frac{1}{S_{d,m}^{(0)}} (S_{d,m} - S_{d,m}^{(0)}) \right] & \leq 0, \\
1 \frac{1}{S_{j,m}} - x_{j,m} - y_{j,m} - H^2 - \left[ 2x_{j,m}y_{m,0} + 2y_{j,m}y_{m,0} \right] & \leq 0,
\end{align*}
\]

(41)\sim (43)

where \( S_{s,m}^{(0)} \) and \( S_{d,m}^{(0)} \) are the Taylor expansion points of \( S_{s,m} \) and \( S_{d,m} \), respectively, and

\[
\begin{align*}
x_{r,m}^{(0)} = (x_m - x_s)^2 + (y_m - y_s)^2, \\
x_{d,m}^{(0)} = (x_m - x_d)^2 + (y_m - y_d)^2, \\
x_{j,m} = x_m - x_j, \\
y_{j,m} = y_m - y_j, \\
(\text{for } m = 1, 2, \ldots, M - 1),
\end{align*}
\]

(44)

where \( x_{r,m} \) and \( y_{r,m} \) are the Taylor expansion points.

**B. OBJECTIVE FUNCTION TRANSFORMATION**

The objective function of Problem 4 is non-convex, and function monotonicity is hard to determine, which is difficult to solve by using KKT method. The successive convex optimization technique (SCA) is used to convert Problem 4 into a series of sub-convex ones. The first-order Taylor expansion is a classic method to approximate the primal optimization problem. With the first-order Taylor expansion, the objective function in (34) can be approximated by (33), shown at the bottom of the previous page. In (33), \( \alpha_{1,m} = P_{g,m}d_{s,e}^2 + \sigma^2 \), \( m = 1, \ldots, M - 1 \); \( S_{e,m} \) is defined in (37); \( S_{e,m}^{(0)} \) is the Taylor expansion point of \( S_{e,m} \); Term 1 is the numerator of \( C_{g,m} \), which is formulated in (9); the sum of Term 2 and Term 3 is the first-order Taylor expansions of the denominator term of \( C_{g,m} \) at \( S_{e,m}^{(0)} \); Term 2 is the value of the denominator term of \( C_{g,m} \) at \( S_{e,m}^{(0)} \); and Term 3 is the first derivative of the denominator term of \( C_{g,m} \) at \( S_{e,m}^{(0)} \).

In Sections IV-C–IV-E, constraints are transformed into their approximated convex forms sequentially.

**C. TRANSMISSION RATE CONSTRAINTS TRANSFORMATION**

Given \( m \), which is the Taylor expansion point of \( S_{g,m} \), constraint (23) is approximated by (45), shown at the bottom of the page. In (45), \( \alpha_{r,m} \) is defined as \( \alpha_{r,m} = k_0P_{r,m}h_{rr}^2 + \sigma^2 \); the denominator of \( C_{s,m} \) is approximated by the sum of Term 4 and Term 5; Term 4 is the value of denominator of \( C_{s,m} \) at \( S_{e,m}^{(0)} \); Term 5 is the first derivative of denominator of \( C_{s,m} \) with respect to \( (w.r.t.) \) \( x_m \) and \( y_m \). \( C_{d,m} \geq \gamma \) in (24) is expressed as

\[
\begin{align*}
\frac{1}{m} \log_2 \left( 1 + \frac{P_{r,m}d_{s,e}^2 + \sigma^2}{S_{d,m}} \right) + \gamma_m \leq 0,
\end{align*}
\]

(46)

where \( S_{d,m} \) is defined in (37). Furthermore, (46) is a convex constraint.

Meanwhile, according to (10), when the time interval \( m \geq 1 \), \( \gamma_m = \min(C_{e,m}, C_{d,m}) \). Since \( \gamma \) is the tight lower bound of \( C_{d,m} \) and \( C_{d,m} \) is smaller than the lower bound of \( C_{d,m} \), rate constraint in (15) can be converted into

\[
\gamma \leq C_{d,m}.
\]

(47)

Additionally, (16) can be approximated by (48), shown at the bottom of the next page, which is in a convex form.

**D. INFORMATION CAUSALITY CONSTRAINTS TRANSFORMATION**

By utilizing the first-order Taylor approximation method for \( C_{e,m} \) and \( C_{d,m} \) in (17), constraint (17) can be rewritten as (49), shown at the bottom of the next page, where \( \alpha_{r,m} = k_0P_{r,m}h_{rr}^2 + \sigma^2 \).

Note that Term 6 and Term 7 in (49) make constraint (49) non-convex. The first-order Taylor expansion method is
applied here to approximate (49) into a convex constraint, which is given as

$$
\sum_{m=1}^{i} B \log_2 \left( P_{g,m} S_{s,m} + P_{g,m} S_{g,m} + \alpha_{r,m} \right) - \phi_1 \geq \phi_2. \quad (50)
$$

Given the Taylor expansion point \((S_{g,m}^{(0)}, S_{d,m}^{(0)})\), Term 6 and Term 7 are approximated by \(\phi_1\) and \(\phi_2\) given as below

$$
\phi_1 = \sum_{m=1}^{i} B \log_2 \left( P_{g,m} S_{g,m}^{(0)} + \alpha_{r,m} \right),
$$

$$
\phi_2 = \sum_{m=1}^{i} B \log_2 \left( 1 + \frac{B P_{r,m} S_{s,m}^{(0)}}{P_{g,m} S_{g,m}^{(0)} + \alpha_{r,m}} \right)
+ \sum_{m=1}^{i} B \frac{P_{r,m} S_{g,m}^{(0)} - S_{s,m}^{(0)}}{P_{g,m} S_{g,m}^{(0)} + \alpha_{r,m}}.
$$

### E. INTERVAL DISTANCE CONSTRAINTS TRANSFORMATION

Clearly, (20) is not in a convex-form. According to the engineering experience, when the speed of UAV is greater than \(v_{ih}\) (\(v_{ih}\) can be around 25 m/s, which is a small value in practice), the power consumption monotonically increases with the speed, and equivalently, \(DD_m\) in (20) can be converted into

$$
DD_m \geq \sqrt{\left(x_m - x_{m-1}\right)^2 + \left(y_m - y_{m-1}\right)^2}, \quad \forall m,
$$

when \(m = 1, 2, \ldots M - 1\), \(\quad (51)\)

$$
D_{x,m}^2 + D_{y,m}^2 \leq D_m', \quad (52)
$$

where \(D_m'\) is the first-order Taylor expansion of \(DD_m\) at the Taylor expansion point \(DD_m^{(0)}\) and

$$
D_m' = \left(DD_m^{(0)}\right)^2 + 2DD_m^{(0)} \left(DD_m - DD_m^{(0)}\right).
$$

With the SCA method, trajectory optimization problem P4 can finally be equivalently solved by iteratively solving P5, given below as:

\[\text{P5}: \quad \min_{T_{tr,m}} V_{tr,m} = q_m P_{tot,m} - \gamma_m - C_{g,m}, \]

\[\quad \text{s.t.} \quad (18), (19), (21), (24), (41) \sim (43), (45), \]

\[\quad (47), (48), (50), (51), \quad (53)\]

#### Algorithm 1: Trajectory Optimization Sub-Problem

**Input:** \(M, T\) and other system parameters in Table II, the maximal variation tolerance \(\epsilon_{tr,m}\) for \(T_{tr,m}\).  
**Output:** Optimal \(T_{tr,m}\), denoted by \(T^*_m\).  
**Initialization:** Set the iteration index of \(\epsilon_{tr,m} = 0\);  
while \(Itr 1 < Itr 1_{max}\) do  
  Itr 1 \(\leftarrow\) Itr 1 + 1;  
  Solve the trajectory optimization sub-problem P5 by KKT;  
  Calculate the objective function \(V_{tr,m}\) in (32) in iteration Itr1, denoted by \(V_{tr,m}(Itr 1)\);  
  if \(\left| V_{tr,m}(Itr 1) - V_{tr,m}(Itr 1-1) \right| < \epsilon_{tr,m} \) then  
    Mark the resulting \(T^*_{tr,m}(r) = T_{tr,m}(Itr 1)\);  
    break;  
  else  
    \(T_{tr,m}^{(0)} = T_{tr,m}^*(Itr 1)\);  
  end  
end

Mark corresponding \(T^*_{tr,m}(r)\).  

where \(T_{tr,m}\) is the set of all variables, including \(x_m, \gamma_m, DD_m, D_{x,m}, D_{y,m}, S_m = \{S_{s,m}, S_{d,m}, S_{j,m}, \forall j \in g, e\}\). In every iteration of \(q_m\) and \(P_m\), the following proposition holds for P5.

**Proposition 2:** Given \(q\) and \(P\), P5 is jointly convex with respect to (w.r.t.) \(T_{tr,m}\). The interior-point method is efficient to achieve the optimum solution.  
**Proof:** Proof can be found in the Appendix A.  

Detailed trajectory optimization algorithm is provided in Algorithm 1. The stopping criterion is either when reaches the maximum iteration index \(Itr 1_{max}\) or the variation of the utility is less than a pre-set threshold \(\epsilon_{tr,m}\).  

### V. POWER OPTIMIZATION PROBLEM TRANSFORMATION

Given the trajectory solution, i.e., \(x_m^*\) and \(\gamma_m^*\), the power optimization problem can be formulated as below:

\[\text{P6}: \quad \min_{\mathcal{P}_m} V_{pw,m} = q_m P_{tot,m} - \gamma_m - C_{g,m}, \]

\[\quad \text{s.t.} \quad (16), (17), (23), (24), \quad (54)\]

$$
\sum_{m=1}^{i} B \log_2 \left( P_{g,m} S_{s,m} + P_{g,m} S_{g,m} + \alpha_{r,m} \right) - \sum_{m=1}^{i} B \log_2 \left( P_{r,m} S_{e,m}^{(0)} + \alpha_{1,m} \right) \geq C_{g,th} \quad (48)
$$

$$
\sum_{m=1}^{i} B \log_2 \left( P_{g,m} S_{s,m} + P_{g,m} S_{g,m} + \alpha_{r,m} \right) \geq \sum_{m=1}^{i} B \log_2 \left( 1 + \frac{P_{r,m} S_{e,m}^{(0)} + \alpha_{1,m}}{P_{g,m} S_{g,m}^{(0)} + \alpha_{r,m}} \frac{P_{g,m} S_{d,m}^{(0)} + \alpha_{1,m}}{P_{g,m} S_{d,m}^{(0)} + \alpha_{r,m}} \right) \quad (49)
$$

Term 1

Term 2

Term 3

Term 6

Term 7
which is obviously non-convex and hard to be solved. It will be approximated into a convex form as below.

### A. OBJECTIVE FUNCTION TRANSFORMATION

With the first-order Taylor expansion, the objective function in (54) can be approximated by (55), shown at the bottom of the page. In (55), Term 8 is the numerator of $C_g,m$; the sum of Term 9 and Term 10 is the first-order Taylor expansion of the denominator of $C_g,m$ at $(P_{r,m}^{(0)}, P_{s,m}^{(0)})$, which is a set of Taylor expansion points of $P_{r,m}$ and $P_{s,m}$. Term 9 is the value of denominator of $C_g,m$; Term 10 is the first derivative of denominator of $C_g,m$ w.r.t. $P_m$; and $S_{e,m}^{(l-1)}, S_{d,m}^{(l-1)}$ are the results of the last trajectory iteration for $S_{e,m}$ and $S_{d,m}$, respectively.

### B. CONSTRAINTS TRANSFORMATION

In this subsection, constraint (23) is converted into its convex form. With the first-order Taylor expansion, $C_{s,m} \geq \gamma_m$ is converted into (56), which can be given as

$$\phi_3 - \phi_4 - \phi_5 \geq \phi_6, m = 1, 2, \ldots, M - 1,$$

where $\phi_3$ is the numerator of $C_{s,m}$; the sum of $\phi_4$ and $\phi_5$ is the first-order Taylor expansion of the denominator term of $C_{s,m}$ at Taylor expansion point $(P_{r,m}^{(0)}, P_{s,m}^{(0)})$. $\phi_4$, $\phi_5$ and $\phi_6$ are formulated as

$$\phi_3 = \text{B} \log_2 \left( P_{r,m} S_{e,m}^{(l-1)} + P_{s,m} S_{e,m}^{(l-1)} + k_0 P_{r,m} |h_{rr}|^2 + \sigma_1^2 \right),$$

$$\phi_4 = \text{B} \log_2 \left( P_{r,m} S_{e,m}^{(l-1)} + P_{s,m} |h_{rr}|^2 \right),$$

$$\phi_5 = \text{B} \log_2 \left( P_{r,m} S_{e,m}^{(l-1)} + k_0 P_{r,m} |h_{rr}|^2 + \sigma_1^2 \right).$$

Similarly, constraints (24) and (16) are transformed into (58) and (59), shown at the bottom of the page, respectively. In (58), Term 11 is the denominator of $C_{d,m}$, which is formulated in (7); the sum of Term 12 and Term 13 is the first-order Taylor expansion of the numerator term of $C_{d,m}$ at the Taylor expansion point $P_{g,m}^{(0)}$. Term 12 is the value of the numerator term of $C_{d,m}$ at the Taylor expansion point $P_{g,m}^{(0)}$; Term 13 is the first derivative of the numerator term of $C_{d,m}$ at the Taylor expansion point $P_{g,m}^{(0)}$. In (59), $(P_{r,m}^{(0)}, P_{s,m}^{(0)})$ is Taylor expansion point of $(P_{r,m}, P_{s,m})$, Term 14 is the numerator of $C_{g,m}$ that is given in (9), and Term 15 is the first-order Taylor expansion of the denominator of $C_{g,m}$.

In addition, information causality constraint (17) is converted into (60) by the first-order Taylor expansion at $(P_{g,m}^{(0)}, P_{r,m}^{(0)})$.

$$C_{s,0} + \sum_{m=1}^{M-1} C_{s,m} \geq \phi_6 - \sum_{m=1}^{M-1} \text{B} \log_2 \left( P_{g,m} S_{e,m}^{(l-1)} + \sigma_2^2 \right),$$

where $C_{s,m}$ is defined in (56), the denominator of $C_{d,m}$ is approximated by the sum of $\phi_6$ and $\phi_7$ given below

$$\phi_6 = \sum_{m=1}^{M-1} \text{B} \log_2 \left( P_{g,m} S_{e,m}^{(l-1)} + \sigma_2^2 \right),$$

$$\phi_7 = \sum_{m=1}^{M-1} \text{B} \log_2 \left( P_{g,m} S_{e,m}^{(l-1)} + \sigma_2^2 \right).$$

With the SCA method, trajectory optimization problem P6 can finally be equivalently solved by iteratively solving P7 presented below:

$$\min_{P_m} q_m P_{tot,m} - \gamma_m - C_{g,m}, \quad m = 1, 2, \ldots, M - 1,$$

subject to (56) ~ (60).
A. CONVERGENCE BEHAVIOUR ANALYSIS

The monotonicity of the upper bound in SCA iterations is first analyzed. According to (31), following formulation is satisfied.

\[
V\left(P_m^{(r-1)}, x_m^{(l-1)}, y_m^{(l-1)}, y_m^{(r-1,l-1)}\right) = -V\left(P_m^{(r-1)}, x_m^{(l-1)}, y_m^{(l-1)}, y_m^{(r-1,l-1)}\right).
\]

VI. JOINT OPTIMIZATION ALGORITHM ANALYSIS

Given \(q_m\), \(P_5\) and \(P_7\) are iteratively optimized until their respective objective functions converge. Then, given the optimized trajectory and power, \(P_3\) can be formulated as

\[
\min_{V_{q,m}(P_m^{(r)}, x_m^{(l)}, y_m^{(l)}, y_m^{(r-1,l)})} q_m P_\text{tot,m} - y_m - C_{g,m}, \quad m = 1, 2, \ldots, M - 1.
\]

Detailed joint optimization algorithm is presented in Algorithm 3. Algorithms 1 and 2 in Algorithm 3 perform cyclic iteration. The stopping criterion is either when reaches the maximum iteration index \(Itr_{q\text{max}}\) or the variation of the utility is less than a pre-set threshold \(\epsilon_{V,m}\).

Note that in each iteration, the upper bound is updated according to Algorithms 1 and 2. In the trajectory optimization, \(P_5\) is optimally solved with given \(q_m\) and \(P_m\). Since \(P_5\) is a maximization problem, in every iteration, the value of the objective function is non-decreasing, and the following formulation holds.

\[
-V\left(P_m^{(r-1)}, x_m^{(l-1)}, y_m^{(l-1)}, y_m^{(r-1,l-1)}\right) \leq -V\left(P_m^{(r-1)}, x_m^{(l-1)}, y_m^{(l-1)}, y_m^{(r-1,l-1)}\right).
\]

While \(P_5\) is solved, \(P_7\) is optimally solved with given \(q_m\) and \(x_m\) and \(y_m\), which is a maximization problem. Following the same analysis as (64), the following formulation holds.

\[
-V\left(P_m^{(r-1)}, x_m^{(l)}, y_m^{(l)}, y_m^{(r-1,l)}\right) \leq -V\left(P_m^{(r-1)}, x_m^{(l)}, y_m^{(l)}, y_m^{(r-1,l)}\right).
\]

According to (63) \~ (65), we have

\[
V\left(P_m^{(r-1)}, x_m^{(l-1)}, y_m^{(l-1)}, y_m^{(r-1,l-1)}\right) \leq V\left(P_m^{(r)}, x_m^{(l)}, y_m^{(l)}, y_m^{(r,l)}\right).
\]

Hence, (66) guarantees that the upper bound is non-increasing during SCA iterations. According to the
aforementioned analysis, it can be claimed that the algorithm converges with finite iteration times.

To have an insight of the convergence rate, the computational complexity is further analyzed in what follows.

**B. COMPLEXITY ANALYSIS**

With the proposed algorithms, trajectory and power management are decomposed and respectively converted into the standard convex optimization problems, which can be efficiently solved with interior point method. Specifically, Dinkebach’s method guarantees that the iteration time for determining $q$ is limited [47]. Furthermore, with the interior-point method applied for $P_5$ and $P_7$, the complexity will be polynomial [48], which is $O(M(Itr_q·Itr_1_{max}/T_2_{r})·\log_2(T_2_{r}))$, where $Itr_1_{max}$ and $Itr_2_{max}$ represent the SCA iteration rounds; $T_1_{r}$ and $T_2_{r}$ iterations are required in solving $P_5$ and $P_7$ with the KKT conditions; $T_2_{r}$ and $T_2_{s}$ are small values; $Itr_q$ represents the maximum iteration number of Dinkebach’s method. The efficient optimization solvers, e.g., Mosek can be applied to solve the joint optimization problem.

**VII. NUMERICAL RESULTS**

In this section, numerical results are provided, and impacts of $P_{r,\max}$ and positions of $T_g$ and $T_e$ are investigated. Additionally, the EE under the SCA will be compared with those under other algorithms.

According to [49], the parameter settings are presented in Table 2, unless otherwise specified. Note that the parameter settings in (12) and (13) are provided in [45].

**TABLE 2. Parameter settings.**

| Parameters | Value | Parameters | Value |
|------------|-------|------------|-------|
| $H$        | 100 m | $T_s$      | (0, 500) m |
| $T_d$      | (2500, 500) m | $T_g$      | (500, 500) m |
| $T_e$      | (2000, 500) m | $\beta$    | 10 MHz |
| $h_{uv}$   | [49] | $\rho$     | 0.012 |
| $\omega$  | 400 dB | $\sigma^2_1, \sigma^2_2, \sigma^2_3$ | [49] |
| $\xi$      | 0.8 | $A$        | 0.1 |
| $\alpha$  | 50 s | $W$        | 400 |
| $U_0$      | 200 | $k_0$      | 0.5 W |
| $f_0$      | 400 Hz | $k_0$ [49] | 0.5 W |
| $V_{max}$  | 60 m/s | $T_2$ [23] | 0.1 watt |
| $P_{r,\max}$ | 10 watts | $P_{s,\max}$ [23] | 1 watt |
| $Itr_1_{max}$ | 1000 | $Itr_2_{max}$ [23] | 1000 |
| $Itr_q_{max}$ | 1000 | $\epsilon_{V,m}, \epsilon_{r,m}, \epsilon_{p,w,m}$ | $10^{-6}$ |

**A. IMPACT OF $T_G$ AND $T_E$ POSITIONS**

As shown in Fig. 2, the optimal power curves and trajectories under $T_g = (500, 500)$ and $T_e = (2000, 500)$ are presented, respectively. According to Fig. 2, five observations can be obtained as below:

1) As shown in Figs. 2(a) and 2(b), from the second to the sixth time interval, the optimal power of ground node $T_s$ takes the value of $p_{s,\min}$ and that of the UAV is $p_{r,\max}$. This is because the distance between UAV and $T_d$ is far while that between UAV and $T_s$ is close, leading to the result that the UAV forwarding capacity (namely, $T_{uv}$-channel capacity) is much smaller than its loading capacity (namely, $T_s$-UAV channel capacity). Therefore, data is accumulated at the UAV in the 1st time interval. To alleviate data accumulation and interference exerted on the other user pair, the power of ground node $T_s$ is reduced while that of the UAV is increased;

2) After the sixth time interval, the optimal power of ground node $T_s$ remains $p_{s,\max}$. This is because the UAV forwarding capacity is higher than its loading capacity when the UAV approaches $T_g$. In this case, to improve the EE, the ground node $T_s$ will increase the transmission power;

3) As the distance between UAV and $T_d$ decreases, the UAV forwarding capacity increases. In contrast, UAV loading capacity decreases. Hence, in every time interval, the data accumulated by UAV is cleared. In this case, $T_g$ does not require a high transmission power to ensure the forwarding ability. Hence, the UAV power decreases, as shown in Fig. 2(b);

4) Furthermore, as shown in Fig. 2(c), when the UAV approaches $T_g - T_e$ pair, the proportion of UAV transmission in EE is large, this is because the long distance between $T_g$ and $T_e$ results in a small $T_g - T_e$ data transmission rate. To ensure the maximum EE, the transmission power of $T_g$ is decreased to reduce the interference exerted on the UAV-relaying transmission;

5) Similarly, as shown in Fig. 2(d), when approaching $T_g$ and $T_e$, UAV avoids $T_g$ to reduce interference and improve the EE.
As shown in Fig. 3, the optimal power curves and trajectories under $T_g = (1500, 500)$ and $T_e = (2000, 500)$ are presented. According to Fig. 3, two observations can be obtained as below:

1) Note that the power of $T_g$ takes the value of $P_{s,\text{max}}$ to maximize $T_g - T_e$ transmission in Fig. 3(c). This is because while $T_g$ and $T_e$ are geographically close, $T_g - T_e$ transmission contributes to a larger proportion in the EE, as compared with UAV-assisted $T_s - T_d$ transmission.

2) As shown in Fig. 3(d), when the UAV approaches $T_g - T_e$ pair, it avoids $T_e$ to reduce the interference on $T_e$. In this case, the UAV remains its minimum power to reduce the interference exerted on $T_g - T_e$ pair, meanwhile satisfies the constraint of (15), which can be observed in Fig. 3(b). At the same time, the UAV is close to $T_d$ and far from $T_s$, the power of $T_s$ takes the value of $P_{s,\text{max}}$ to reduce the interference from $T_g - T_e$ pair and ensure $T_s$-UAV transmission, which can be observed in Fig. 3(a).

**B. IMPACTS OF $P_{s,\text{max}}$ ON THE EE**

In this subsection, the impacts of the maximum power of $T_s$ on the EE are studied.

As shown in Fig. 4(b), as $P_{s,\text{max}}$ increases, the EE significantly increases. This is because as $P_{s,\text{max}}$ increases, as illustrated in Fig. 3(a), the optimal power of $T_s$ takes the value of $P_{s,\text{max}}$, which results in the increase of the optimal power $P_s^*$. Moreover, according to Fig. 4(a), after the 10th time interval, there is no data accumulation, which implies that the UAV forwarding capacity equals the loading capacity, i.e., $\gamma_m = C_{s,m}$ holds. Hence, as $P_{s,\text{max}}$ increases, $\gamma_m = C_{s,m}$ increases, resulting in an increasing EE.

In addition, as shown in Fig. 4(a), as $P_{s,\text{max}}$ increases, the number of accumulated bit increases. This is because the UAV only receives but does not forward data in the first time interval, leading to the bit accumulation at the UAV. Moreover, due to the limited UAV forwarding capacity, as $P_{s,\text{max}}$ increases, the bit number in the first time interval increases, resulting in a slower speed of clearing accumulated bits at the UAV.

**C. ANALYSIS OF RECEIVED, BUFFERED, AND FORWARDED BITS**

In Fig. 5, the accumulated bits in different time intervals are presented. Note that the curve of “Buffered at UAV” represents the bits accumulated at UAV, and the curve of “Forwarded by UAV” represents the bits forwarded by UAV.
at each time interval. As shown in Fig. 5, there is no gap between the curve of “Forwarded by UAV + Buffered at UAV” and the curve of “Received by UAV”, which means that information causality is satisfied. Moreover, consistent with Fig. 4(b), in the 10th time interval, the accumulated bits are approximately cleared, which implies that the bits forwarded by UAV data are same to that of being received.

D. ALGORITHM PERFORMANCE COMPARISONS

In Fig. 6, performance comparisons with other benchmarks, including “FDR-Exhaustive Search”, “FDR-Exact utility”, “FDR-Genetic algorithm”, “FDR-Random selection”, and “HDR-Exhaustive Search” are demonstrated as $T_g$ and $T_e$ take different positions. The “FDR-Exhaustive Search” result is achieved by traversing all feasible parameters to find the optimal solution under the FDR scheme; the “FDR-Exact utility” is obtained by substituting the sub-optimal “FDR-SCA” solution into the exact utility in (22); the “FDR-Genetic algorithm” is a heuristic algorithm for finding the sub-optimal solution under the FDR scheme; the “FDR-Random selection” algorithm is achieved by multiple random selections and calculating the mean value under the FDR scheme; the “HDR-Exhaustive Search” algorithm is achieved by traversing all feasible parameters to find the optimal solution under the HDR scheme.

The following observations can be achieved: 1) no matter how the positions of $T_g$ and $T_e$ vary, the EE obtained with our algorithm matches well with the “FDR-Exhaustive Search” algorithm; moreover, compared with “FDR-Exact utility”, the gap between these two algorithms is less than 2%. Hence, the approximation of the proposed algorithm is tight to the primal optimization problem. The above verifies the validity of our optimization method; 2) Due to the randomness of the “FDR-Genetic algorithm” and “FDR-Random selection”, the EEs of these two algorithms are significantly lower than that of the proposed algorithm; 3) Note that the EE of “FDR-Exhaustive Search” is almost twice that of “HDR-Exhaustive Search”. This is because by enabling simultaneous transmission and receiving, the FD improves data transmission rate and further increases the EE; 4) As the distance between $T_g$ and $T_e$ increases, the channel capacity $C_{g,m}$ decreases, and the EEs under all algorithms decrease.

E. CONVERGENCE BEHAVIOUR

Fig. 7 shows the iterative curve of the joint power and trajectory optimization. It contains the curves of three sub-problems, corresponding to the trajectory optimization sub-problem (P5), power optimization sub-problem (P6), and $q$ iteration (see line 3, 5, 6 and 7 in Algorithm 2, respectively). Following four observations can be obtained:

1) The first curve segment represents the iterative process of the trajectory sub-optimization problem. It can be seen that the iteration can quickly converge;
2) The second curve segment represents the iterative process of the power sub-optimization problem. The convergence solution of the trajectory optimization problem (corresponding to the first curve segment) is set as prior known constants in the power optimization subproblem. It can be seen that the performance is improved at the transition between the first and second segments. For each sub-convex
optimization problem of power optimization, the KKT condition is used to solve it internally. It can be seen that the internal iteration of KKT can quickly converge;

3) The third curve segment represents the iterative process of $q$ value in the joint power trajectory optimization process. When $q$ value iteration is completed, a new iteration of the trajectory optimization problem will start;

4) In the entire optimization iteration process, energy efficiency is non-decreasing, and the three sub-optimization problems can quickly converge through loop iterations, which implies that the proposed algorithm is efficient.

VIII. CONCLUSION
The EE maximization problem of UAV-relaying 5G spectrum sharing wireless networks has been investigated. Online interference coordination approach for energy efficient FD UAV relaying networks was investigated. Power management and UAV flight trajectory have been optimized to maximize the EE under the constraints of information causality and transmission rate. The optimization problem was sequentially decomposed and converted into two sub convex optimization problems. For each sub-problem, the successive convex approximation algorithm was exploited, and the convergence behaviour was also demonstrated. Numerical results demonstrated that the proposed algorithm converges well, and the gap between the exact and approximate utility is less than 2%. Additionally, the EE of the proposed algorithm is about 30% and 46% higher than those of the genetic algorithm and the half-duplex scheme, simulation results show that our scheme outperforms the existing schemes in convergence speed (and whatever else), which suggests the superiority of our method in this scenario.

APPENDIX
A. THE PROOF OF PROPOSITION 2
First, prove the convexity of (33), which is the objective function of $P5$. Note that it has been approximated by the Taylor expansion in Section IV-A. For ease of Hessian matrix notations, the variables $S_{e,m}$, $DD_m$, $\lambda_m$, $y_m$, $D_{x,m}$, $S_{x,m}$, $S_{e,m}$ are represented by $T_{m,1}$, $T_{m,2}$, $T_{m,3}$, $T_{m,4}$, $T_{m,5}$, $T_{m,6}$, $T_{m,7}$, $T_{m,8}$, $T_{m,9}$, $T_{m,10}$, respectively. Then the Hessian matrix of the objective function in $P5$ can be denoted by $H$, where $\nabla^2f(x, y)$ represents the second-order partial derivative of $f$ w.r.t. $x$ and $y$. Note that

$$\nabla^2V_{tr,m}(T_{m,1}) = \frac{B}{lo^2}(p^{m}_{pr,m} \cdot e^{-x} + p^{m}_{pr,m} \cdot e^{-y} + \sigma^2_2) > 0,$$

$$\nabla^2V_{tr,m}(T_{m,2}) = \frac{P_0}{U_{up}} \frac{6}{T^2/M} + \frac{2P_0 T}{(\rho D_m)^3} + \frac{3P_0 T \rho A D_m}{T^3 M^3} > 0,$$

and the rest of the elements of $H$ are all zero, which imply that $H$ is a positive semi-definite matrix. Hence, (33) is jointly convex w.r.t. $T_{tr,m}$.

Next, convexities of the constraints are proved. According to the above, constraint (48) is convex. With the same method we can find that constraints (45), (47), and (50) are convex as well. (41) ~ (43) and (51) are linear functions. Furthermore, constraints (18) and (21) are equality constraints, and (19) is a linear inequality constraint. According to (46), (24) is a convex constraint. Hence, optimization problem (33) is convex and constraints (18), (19), (21), (24), (45), (47), (48), (41) ~ (43), (50) and (51) are convex, $P5$ is jointly convex w.r.t. $T_{tr,m}$. Proposition 2 is proved.

B. THE PROOF OF PROPOSITION 3
The convexity of the objective function is first proved. Following the same method in the convexity proof of (33), the Hessian matrix of the objective function in $P7$ is positive semi-definite, which implies that (55) is convex w.r.t. $P_m$.

Next, the convexities of the constraints are further proved. For the constraints, in (56), as the second derivative of $\phi_1$ is less than 0, $\phi_1$ is concave w.r.t. $P_m$, $\phi_2$ is a constant, and $\phi_3$ is a linear function w.r.t. $P_m$. Hence, (56) is a convex constraint. Similarly, it can be known that constraints (58) ~ (60) are all convex constraints. As the optimization problem (55) is convex and the constraints (56) ~ (60) are all convex, $P7$ is jointly convex w.r.t. $P_m$. Proposition 3 is proved.

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