Joint Optimization of Trajectory and Communication in Multi-UAV Assisted Backscatter Communication Networks

YU DU¹, ZIJING CHEN², JIANJUN HAO², AND YIJUN GUO², (Member, IEEE)

¹Business School, Beijing Language and Culture University, Beijing 100083, China (e-mail: dyu@blcu.edu.cn)
²Beijing Key Laboratory of Network System Architecture and Convergence, Beijing University of Posts and Telecommunications, Beijing 100876, China (e-mail: chenzijing@bupt.edu.cn, jjhao@bupt.edu.cn, guoyijun@bupt.edu.cn)

ABSTRACT This paper investigates a multiple unmanned aerial vehicle (multi-UAV) assisted backscatter communication network (BCN), where multiple UAVs are employed to transmit RF carriers to as well as collect data from multiple backscatter sensor nodes (BSNs) deployed on the ground. We formulate an optimization problem to maximize the max-min rate of the BCN by jointly optimizing three blocks of variables, i.e., the UAVs’ trajectories, the UAVs’ transmission power and the BSNs’ scheduling. The BSNs’ sequential energy constraints are innovatively considered in our work. However, the formulated optimization problem is difficult to be solved due to its non-convexity and combinatorial nature. To this end, we use the block coordinate descent (BCD) method and successive convex approximation (SCA) technique. Numerical results show the impact of the BSNs’ sequential energy constraint on the designed UAV trajectories and verify the gain of the proposed design in the max-min rate as compared to a benchmark scheme with UAV trajectory not optimized.

INDEX TERMS multi-UAV assisted communication, backscatter communication network, joint trajectory and communication design, trajectory optimization.

I. INTRODUCTION

The Internet-of-Things (IoT) provides ubiquitous connectivity among billions of devices [1] [2], and has various applications, such as industrial automation, precision agriculture, and smart cities [3] [4]. Backscatter communication is a promising technology for future IoT. The sensor nodes (SNs) in backscatter communication are enabled to transmit information by modulating incident sinusoidal carriers or ambient radio-frequency (RF) carriers instead of using traditional power-hungry RF transmitters [5]. To this end, backscatter communication significantly reduces SNs’ circuit power consumption and prolongs SNs’ service duration [6] [7], thus provides an energy efficient solution for communicating with IoT devices.

In many backscatter communication networks (BCNs), dedicated RF power sources are deployed as carrier emitters (CE) to extend the communication range of backscatter sensor nodes (BSNs) [8]. However, the traditional BCNs with CEs and backscatter receivers (BRs) fixed on the ground still face the double channel-attenuation challenge. For applications in remote areas and restricted regions, such as intelligent agriculture in large farms and fauna and flora protection in national parks, the double channel-attenuation challenge will lead to serious issues of constrained communication range and low data rates [9].

Unmanned aerial vehicles (UAVs) assisted wireless communication has attracted growing research interests from both academy and industry, due to its wide coverage, high mobility, low operational costs and high probability of line-of-sight (LoS) links from air to ground [10]–[14]. Motivated by the superiority of UAVs in assisting wireless communications, many studies try to introduce UAVs to backscatter communication networks. In [15] [16], Hua et al. investigated a UAV-assisted BCN where a UAV operates as both a carrier emitter and a relay, and maximized the throughput of a backscatter communication system by optimizing the UAV’s trajectory, time allocation and backscattering coefficients.
A similar scenario was addressed in [17], where the authors studied the optimal UAV data collection location for maximizing energy efficiency. Besides, the authors in [18] considered the case that a UAV is deployed as a flying backscatter receiver in the BCN, which also consists of multiple BSNs and CEs on the ground. The energy efficiency of BCN is maximized by jointly optimizing the UAV’s trajectory, BSNs’ scheduling, and CEs’ transmission power. In some other works, the UAV is considered to act as both a flying CE and a flying BR. Specifically, in [19], the BSNs adopted a non-orthogonal-multiple-access (NOMA) scheme to transmit information to the BR. The optimal UAV flying altitude was optimized to maximize the number of successfully decoded bits in the uplink while minimizing the flight time. In [20], the authors maximized the uplink fairness-secretary-rate of BSNs by optimizing the backscattering coefficients along with the UAV trajectory.

However, most of the existing researches on UAV-assisted BCN only consider the case of exploiting one single UAV to assist communication, which is far away from practical deployment, especially when considering a large coverage area. In fact, although a single UAV has demonstrated its advantages in performance enhancement for wireless networks [21][22], it still has limited capability in general due to the practical size, weight and power (SWAP) constraints [23]. Therefore, for the scenario with a large coverage area or a large number of BSNs, it is significant to employ multiple UAVs to assist the communication cooperatively.

Recently, there have been some works considering multi-UAV assist backscatter communication networks. In [24], the optimal deployment of multiple UAVs were investigated to minimize the transmission power of ground IoT devices. However, this work only considered deploying UAVs in fixed positions, which had not utilize the UAVs’ advantage of movement. In [25], the authors proposed a single-agent deep option learning as well as a multi-agent deep option learning to design the trajectory of multiple rechargeable UAVs for collecting data from clustered BSNs in the shortest total flight time. However, the authors divided the whole network into several flying areas in advance, and each UAV was only allowed to fly in its own area. Thus, the multi-UAV trajectory design problem has been simply decoupled into the sum of several single-UAV trajectory design problems, which ignored the interaction effect between multiple UAVs. Therefore, the problem of multi-UAV trajectory design in backscatter communication networks has not been studied well.

Moreover, the backscatter sensor nodes usually harvest energy from the incident RF carrier signals, which is used to support the circuit operation as well as the signal backscattering. To this end, for an arbitrary time slot, the accumulated consumed energy should not exceed the available energy, which is decided by the accumulated harvest energy and the initial energy. However, such relationships have not been considered by the state of the art yet.

In this paper, we study a multi-UAV assisted backscatter communication network as shown in Figure 1, where multiple UAVs are employed to transmit RF carriers to as well as collect data from multiple backscatter sensor nodes deployed on the ground. We aim to maximize the minimum average rate among all BSNs. The main contributions are summarized as follows.

- First, we innovatively formulate the joint optimization problem of trajectory and communication involving multiple UAVs to providing service for multiple backscatter sensor nodes. The sequential energy constraints which restrict the relationship between the consumed energy and the harvest energy at each time slot for BSNs have been considered for the first time.
- Second, we solve the formulated non-convex problem via dividing it into three sub-problems. The successive convex approximation (SCA) technique and the block coordinate descent (BCD) method are applied to tackle the sub-problems, and an algorithm is proposed to alternately solved the sub-problems until it converges.
- Third, by numerical results, we show the impact of the BSNs’ sequential energy constraint on the designed UAV trajectories and verify the gain of the proposed design in the max-min rate as compared to a benchmark scheme with UAV trajectory not optimized.

The remainder of the paper is organized as follows. Section II introduces the system model for the multi-UAV assisted backscatter communication network, and formulates the optimization problems. Section III proposes an efficient alternating algorithm to solve the prob-
lem. Section VI provides numerical results, and Section V summarizes the whole work finally.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. SYSTEM MODEL

As shown in Figure 1, we consider a multi-UAV assisted backscatter communication network, where \( M \geq 1 \) rotary-wing UAVs are employed to transmit carrier signals to and collect backscattered signals from \( K \geq 1 \) BSNs which are randomly distributed on the ground. The UAV set and BSN set are denoted by \( \mathcal{M} \) and \( \mathcal{K} \), respectively, where \( |\mathcal{M}| = M \) and \( |\mathcal{K}| = K \).

Without loss of generality, we consider a two-dimensional Cartesian coordinate system. The location of BSN \( k \in \mathcal{K} \) is denoted by \( \mathbf{w}_k \in \mathbb{R}^{2 \times 1} \). The exact locations of the BSNs on the ground are assumed to be known by a central controller of the system. The UAV is assumed to fly at a fixed altitude \( H \) above the ground, and the time-varying horizontal coordinate of UAV \( m \in \mathcal{M} \) is denoted by \( \mathbf{q}_m(t) = [x_m(t), y_m(t)]^T \in \mathbb{R}^{2 \times 1} \), with \( 0 \leq t \leq T \). For ease of exposition, the period \( T \) is discretized into \( N \) equal time slots, with length \( T_s = \frac{T}{N} \) is chosen to be sufficiently small such that a UAV’s location is considered as approximately unchanged within each time slot even at the maximum speed \( V_{\text{max}} \). As a result, the trajectory of UAV \( m \) can be approximated by a \( N \)-length sequence \( \mathbf{q}_m[n] = [x_m[n], y_m[n]]^T \), \( n = 1, \ldots, N \). During the \( n \)-th time slot, the distance between UAV \( m \) and BSN \( k \) is \( d_{m,k}[n] = \sqrt{||\mathbf{q}_m[n] - \mathbf{w}_k||^2 + H^2} \).

In this backscatter communication network, the UAVs serve as both carrier emitters and backscatter receivers. For data collection, the UAVs transmit signals to activate the BSNs. If a BSN is activated, it backscatters the received signals for energy harvesting, i.e., \( h_{k,m}[n] \) is the channel power gain from UAV \( m \) to BSN \( k \) during time slot \( n \). The received signal at BSN \( k \) in time slot \( n \) can be expressed as

\[
y_k[n] = x_m[n] h_{m,k}[n] + \sum_{m' \neq m} x_{m'}[n] h_{m',k}[n],
\]

where \( x_m[n] \) is the RF signal transmitted by UAV \( m \), with power \( \mathbb{E}\{ |x_m[n]|^2 \} = P_m[n] \), the second item in the righthand of (1) represents the co-channel interference caused by the transmitting of all the other UAVs in time slot \( n \). Note that the noise received at the BSN is neglected because the BSN’s circuit only consists of passive components and involves little signal processing operation \([27]–[29]\).

If BSN \( k \) is activated by UAV \( m \) in time slot \( n \), i.e., \( \alpha_{m,k}[n] = 1 \), it backscatters the received signals \( y_k[n] \). The backscattered signal is expressed as

\[
y_k^b[n] = \sqrt{\phi_k} b_k[n] y_k[n],
\]

where \( b_k[n] \) is the information bit to be transmitted by BSN \( k \) in time slot \( n \) with \( \mathbb{E}\{ |b_k[n]|^2 \} = 1 \). \( \phi_k \) represents the backscatter coefficient which is adjusted for adaptively switching between the backscattering mode and the energy harvesting mode. In practice, BSNs have finite reflecting status which are once implemented and then fixed. In this paper, following the parameters of most commercial tags [30], we assume that each BSN either fully backscatters its incident signals or uses all the incident signals for energy harvesting, i.e., \( \phi_k = 1, \forall k \). Thus, we have \( y_k^b[n] = b_k[n] y_k[n] \).

The received signal at UAV \( m \) is given by

\[
z_m[n] = y_k^b[n] h_{m,k}[n] + \sum_{k'=1, k' \neq k}^K \left( \sum_{m=1}^M \alpha_{m,k'}[n] \right) y_{k'}^b[n] h_{m,k'}[n] + w[n],
\]

1) Achievable average rates of BSNs

The transmit power of UAV \( m \in \mathcal{M} \) in time slot \( n \) is denoted by \( P_m[n] \), which is subject to the constraint \( 0 \leq P_m[n] \leq P_{\text{max}} \), with \( P_{\text{max}} \) denoting the peak UAV transmission power. By assuming line-of-sight (LoS) channels between the UAV and BSNs, \(^1\) the channel power gain from UAV \( m \) to BSN \( k \) during time slot \( n \) is given by \( h_{m,k}[n] = \rho_0 d_{m,k}^{\tau_1} [n] = \frac{\rho_0}{\|\mathbf{q}_m[n] - \mathbf{w}_k\|^2 + H^2} \), where \( \rho_0 \) is the channel power gain at a reference distance of 1 meter (m). Since we consider that the UAVs and BSNs are equipped with a single antenna and the positions of UAVs are unchanged during time slot \( n \), the reverse link from BSN \( k \) to UAV \( m \) can be assumed to be equal with the link from UAV \( m \) to BSN \( k \), i.e., \( h_{k,m}[n] = h_{m,k}[n] \).

In this paper, the NLoS components have limited impact on the transmission between the UAVs and BSNs and can be ignored for two reasons. First, the BCNs are usually deployed in an open space, such as farmland, public parks. With the minimum flying height limitation for UAVs, the probability of NLoS is relatively small. Second, the UAVs tend to fly to the locations above each BSN in turn for better communication performance, making the probability of LoS larger.
where $y_k^b[n]h_{m,k}[n]$ is the signal backscattered from BSN $k$, $w[n]$ denotes the noise, which follows the circularly symmetric complex Gaussian (CSCG) distribution, i.e., $w[n] \sim \mathcal{C}\mathcal{N}(0, \sigma^2)$. The second item in the right-hand of (3) represents the sum of signals backscattered from the active BSNs except BSN $k$, with the sum item $\sum_{m=1}^{M} \alpha_{m,k}[n]$ indicating the state of BSN $k'$ in time slot $n$, i.e., BSN $k'$ is activated by some UAV if $\sum_{m=1}^{M} \alpha_{m,k'}[n] = 1$, otherwise, $\sum_{m=1}^{M} \alpha_{m,k}[n] = 0$. For the purpose of expose, we assume that the signal interference from other BSNs will be ignored in this paper. This assumption is reasonable since a UAV always tends to activate the nearest BSN [25]. As such, $z_m[n]$ can be approximated by

$$z_m[n] = y_{m}^b[n]h_{m,k}[n] + w[n] = b_k[n]x_m[n]h_{m,k}^2[n] + \sum_{m'=1}^{M} x_{m'}[n]h_{m',k}[n] + w[n].$$

(4b) is obtained by substituting (1) and (2) into (4a).

Then, the received signal-to-interference-plus-noise ratio (SINR) at UAV $m$ can be expressed as

$$\gamma_{m,k}[n] = \frac{p_m[n]h_{m,k}^2[n]}{\sum_{m'=1}^{M} p_{m'}[n]h_{m',k}[n]h_{m,k}[n] + \sigma^2}.$$  

(5)

The achievable rate of user $k$ in time slot $n$ in bits/second/Hertz (bps/Hz) is given by $R_{m,k}[n] = \log_2 (1 + \gamma_{m,k}[n])$. Thus, the achievable average rate of BSN $k$ over $N$ time slots is given by

$$R_k = \frac{1}{N} \sum_{n=1}^{N} R_{m,k}[n] = \frac{1}{N} \sum_{n=1}^{N} \alpha_{m,k}[n] \log_2 (1 + \gamma_{m,k}[n]).$$  

(6)

2) Sequential energy constraints of BSNs

For each BSN $k \in K$, if it is not activated by any UAV in time slot $n$, i.e., $\sum_{m=1}^{M} \alpha_{m,k}[n] = 0$, it will harvest energy from the incident signal. Let $\eta \in [0, 1]$ be the BSN’s RF-energy harvesting efficiency. Then, the energy harvested by BSN $k$ in time slot $n$ can be expressed as

$$P_{hav,k}[n] = \eta \sum_{m=1}^{M} p_m[n]h_{m,k}[n].$$  

(7)

The energy harvested by a BSN is used in two ways. One part is used to power the BSN’s circuit power consumption, and the remaining energy is used to backscatter the BSN’s information data [27] [31]. Assuming that the signal processing delay at the BSN is one time slot, we have the following sequential energy constraint for BSN $k$ to keep working

$$E_0 + \sum_{n=1}^{n-1} (1 - \alpha_k[n])P_{hav}[n]T_s \geq nT_sP^c + \sum_{n=1}^{n} \alpha_k[n]T_sP^b, \quad n = 1, \ldots, N,$$

(8)

where $E_0$ denotes the initial energy of each BSN, $\alpha_k[n] = \sum_{m=1}^{M} \alpha_{m,k}[n]$ indicates the state of BSN $k$ in time slot $n$. Specifically, BSN $k$ is activated by a UAV and it backscatters the received signals in time slot $n$ if $\alpha_k[n] = 1$, otherwise it harvests energy from the incident signal. $P^c$ and $P^b$ denote the power consumption of each BSN for circuit operation and for signal backscattering, respectively. The right-hand-side of (8) stands for the BSN’s total circuit power consumption from the beginning to time slot $n$, which can not be more than the total energy harvested by the BSN from the beginning to time slot $n - 1$ as given in the left-hand-side of (8).

B. PROBLEM FORMULATION

For the above multi-UAV assisted backscatter communication network, we focus on the overall performance of all the BSNs. Therefore, we jointly optimize the UAVs’ trajectories, transmit power, and the BSN scheduling to maximize the max-min rate of $K$ BSNs while satisfying the sequential energy constraint for the BSNs. By defining $Q = \{q_{m}[n], \forall m, n\}$, $P = \{p_{m}[n], \forall m, n\}$, and $A = \{\alpha_{m,k}[n], \forall m, k, n\}$, the optimization problem is formulated as

$$\begin{align*}
(P1): & \quad \max_{R_{fair},Q,P,A} R_{fair} \\
\text{s.t.} & \quad R_k \geq R_{fair}, \quad \forall k, \\
& \quad E_0 + \eta T_s \sum_{n=1}^{M} \sum_{m=1}^{n} (1 - \alpha_k[n])p_m[n]h_{m,k}[n] \\
& \quad \geq nT_sP^c + \sum_{n=1}^{n} \alpha_k[n]T_sP^b, \quad \forall n, \forall k, \\
& \quad ||q_{m}[n] - q_{m}[n - 1]|| \leq \min(T_sV_{max}, \Delta_{max}), \quad \forall n, \forall m, \\
& \quad ||q_{m}[n] - q_{j}[n]|| \geq D_{safe}, \quad \forall n, \forall m \neq j, \\
& \quad 0 \leq p_{m}[n] \leq P_{max}, \quad \forall n, \forall m, \\
& \quad \sum_{k=1}^{K} \alpha_{m,k}[n] \leq 1, \quad \forall n, \forall m, \\
& \quad \sum_{n=1}^{M} \alpha_{m,k}[n] \leq 1, \quad \forall n, \forall k.
\end{align*}$$

(9)

VOLUME 4, 2016

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/
where \( R_{\text{fair}} = \min_{k \in K} R_k \) is the minimum rate of \( K \)
BSNs, \((9c)\) is the sequential energy constraint discussed in Section II-A, \((9d)\) restricts both the UAV speed and the
finite-sum approximation error introduced by the
time discretization for UAVs’ trajectories, with \( V_{\text{max}} \)
and \( \Delta_{\text{max}} \) denoting the maximum UAV speed and the
discretization segmentation length, respectively., \((9e)\) ensures collision avoidance between different UAVs
with \( D_{\text{safe}} \) denoting the minimum inter-UAV distance.

III. PROPOSED ALGORITHM

In this section, we propose an efficient iterative algo-
rithm to solve problem \((P1)\) based on the BCD method
[32] and the SCA technique [33]. Specifically, we split
the optimization variables into three blocks, i.e., the
UAVs’ trajectories \( Q \), the UAV transmit power \( P \) and
the BSN scheduling \( A \). In each iteration, the three blocks
of variables are optimized concomitantly, corresponding
to three optimization subproblems, respectively. Also, the
convergence and complexity of the proposed algorithm
are analyzed.

A. UAV TRAJECTORY OPTIMIZATION

Given UAV transmit power \( P \) and BSN scheduling \( A \),
the UAVs’ trajectories \( Q \) can be optimized by solving the
following problem

\[
\begin{align*}
\text{(P2)}: \quad & \max_{R_{\text{fair}}, Q} R_{\text{fair}} \\
\text{s.t.} \quad & (9b), (9c), (9d), (9e).
\end{align*}
\]

Note that problem \((P2)\) is neither a concave or a quasi-
concave maximization problem due to the non-convex
constraints in \((9b), (9c)\) and \((9e)\). In the following, we
adopt the successive convex optimization technique to
solve the trajectory optimization problem.

First, we reformulate \( R_{m,k}[n] \) in constraint \((9b)\) as

\[
R_{m,k}[n] = \log_2 \left( 1 + \frac{p_{m}[n]h_{m,k}^2[n]}{\sum_{m', m'' \neq m} p_{m'}[n]h_{m',k}[n]h_{m,k}[n] + \sigma^2} \right)
\]

\[
= \hat{R}_{m,k}[n] - \log_2 \left( \sum_{m' = 1}^{M} p_{m'}[n]h_{m',k}[n]h_{m,k}[n] + \sigma^2 \right)
\]

where

\[
\hat{R}_{m,k}[n] = \log_2 \left( \sum_{m' = 1}^{M} p_{m'}[n]h_{m',k}[n]h_{m,k}[n] + \sigma^2 \right)
\]

By substituting \((11)\) and \((12)\), constraint \((9b)\) can be transformed into

\[
\frac{1}{N} \sum_{n=1}^{N} \sum_{m=1}^{M} \alpha_{m,k}[n] \left( \hat{R}_{m,k}[n] - \log_2 \left( \sum_{m' = 1}^{M} p_{m'}[n]h_{m',k}[n]h_{m,k}[n] + \sigma^2 \right) \right) \geq R_{\text{fair}}, \quad \forall k.
\]

By Lemma 1.

Theorem 1. \( \hat{R}_{m,k}[n] \) as given in \((12)\) is jointly convex with respect to \( x_1, \ldots, x_M \) given \( x_1, \ldots, x_M \geq 0 \).

Proof: See Appendix A.

Next, we apply the successive convex optimization to
constraints \((14b), (14c), (9c)\) and \((9e)\) in problem \((P2.1)\)
to tackle the non-convexity.

\[
\text{Lemma 1:} \quad \text{Define function } f_m(x_1, \ldots, x_M) \text{ as}
\]

\[
f_m(x_1, \ldots, x_M) = \ln \left( \sum_{m' = 1}^{M} \frac{c_1}{(x_{m'} + c_2)(x_m + c_2) + c_3} \right)
\]

where \( c_1, c_2 > 0 \) and \( c_3 \) are pre-defined constants.

By Lemma 1, \( \hat{R}_{m,k}[n] \) as given in \((12)\) is jointly convex with respect to \( \{Q_1[n] - w_k]\|^2, \ldots, \{Q_M[n] - w_k]\|^2 \). For given local points \( \{q_1[n], \ldots, q_M[n]\} \) in
r-th iteration, we can use the first-order Taylor expan-
sion to get the lower bound of \( \hat{R}_{m,k}[n] \) [10], which is
expressed as

\[
\hat{R}_{m,k}[n] \geq A_{m,k}[n] \left( \{Q_1[n] - w_k]\|^2 - \{q_1[n] - w_k]\|^2 \right)
\]

\[
- \sum_{m' = 1}^{M} B_{m',k}[n] \left( \{Q_M[n] - w_k]\|^2 - \{q_M[n] - w_k]\|^2 \right)
\]

VOLUME 4, 2016

5
where \( A_{m,k}^r[n] \), \( B_{m,k}^r[n] \) and \( C_{m,k}^r[n] \) are constants which are given by
\[
A_{m,k}^r[n] = \sum_{m'=1}^{M} \left( D_{m,k}^r[n] + \sigma^2 \right) f_{d^2}(q_{m}^r[n], w_k) f_{d^2}(q_{m}^r[n], w_k),
\]
\[
B_{m,k}^r[n] = \frac{p_m[n] \rho^2 \log_2(\epsilon)}{\left( D_{m,k}^r[n] + \sigma^2 \right) f_{d^2}(q_{m}^r[n], w_k) f_{d^2}(q_{m}^r[n], w_k)},
\]
\[
C_{m,k}^r[n] = \log_2 \left( D_{m,k}^r[n] + \sigma^2 \right),
\]
with function \( f_{d^2}() \) defined as \( f_{d^2}(x,y) = \|x - y\|^2 + H^2 \), and constant \( D_{m,k}^r[n] \) given by
\[
D_{m,k}^r[n] = \sum_{i=1}^{M} p_i[n] \| f_{d^2}(q_{i}^r[n], w_k) f_{d^2}(q_{i}^r[n], w_k) \|.
\]

In constraint (14c), \( \|q_m[n] - w_k\|^2 \) is a convex function with respect to the variable \( q_m[n] \). By applying the first-order Taylor expansion at given point \( q_m^r[n] \), we have the following inequalities
\[
\|q_m[n] - w_k\|^2 \geq 2(q_m^r[n] - w_k)^T (q_m[n] - q_m^r[n]) + \|q_m^r[n] - w_k\|^2.
\]

In constraint (9c), \( h_{m,k}[\hat{n}] \) is convex with respect to \( \|q_m[n] - w_k\|^2 \). By applying the first-order Taylor expansion at given point \( q_m^r[\hat{n}] \), we obtain the lower bound of \( h_{m,k}[\hat{n}] \), which is given by
\[
h_{m,k}[\hat{n}] = \frac{\rho_0}{\|q_m[n] - w_k\|^2 + H^2} \geq \frac{\rho_0 (\|q_m[n] - w_k\|^2 - \|q_m^r[n] - w_k\|^2)}{\left( \|q_m^r[n] - w_k\|^2 + H^2 \right)^2} + \frac{\rho_0}{\|q_m^r[n] - w_k\|^2 + H^2} \approx h_{m,k}[\hat{n}].
\]

Constraint (9e) can be equivalently transformed into
\[
\|q_m[n] - q_j[n]\|^2 \geq D_{safe}^2, \quad \forall n, \forall m \neq j.
\]
and by applying the first-order Taylor expansion to \( \|q_m[n] - q_j[n]\|^2 \) at given points \( \{q_m^r[n], q_j^r[n]\} \), we obtain the following lower bound as
\[
\|q_m[n] - q_j[n]\|^2 \geq 2(q_m^r[n] - q_j^r[n])^T (q_m[n] - q_j[n]) - \|q_m^r[n] - q_j^r[n]\|^2.
\]

Then, given local points \( Q^r = \{q_m^r[n], \forall m, n\} \) in the \( r \)-th iteration, problem (P2.1) can be approximated as
\[
(P2.2) : \max_{R_{fair}} Q_s R_{fair}^r
\]
where

\[
R_{m,k}[n] = \log_2 \left( \sum_{m', t \neq m} p_{m'}[n] h_{m', k}[n] h_{m,k}[n] + \sigma^2 \right).
\]

Again, we use the successive convex optimization technique to handle the non-convexity of constraint (9b). In particular, we note that \(R_{m,k}[n]\) as given in (26) is concave with respect to \(p_{m'}[n]\). With any given local point \(p'_{m'}[n]\), we can use the first-order Taylor expansion to get the upper bound of the concave function \(R_{m,k}[n]\), which is expressed as

\[
R_{m,k}[n] = \log_2 \left( \sum_{m', t \neq m} p_{m'}[n] h_{m', k}[n] h_{m,k}[n] + \sigma^2 \right)
\leq \sum_{m', t \neq m} p_{m'}[n] h_{m', k}[n] h_{m,k}[n] + \sigma^2
+ \log_2 \left( \sum_{m', t \neq m} p_{m'}[n] h_{m', k}[n] h_{m,k}[n] + \sigma^2 \right)
\triangleq \hat{R}_{m,k}^{ub}[n], \quad \forall k, m, n.
\]

Then, given local points \(P^r = \{p'_{m}[n], \forall m, n\}\) in the \(r\)-th iteration, problem (P3) can be approximated using the upper bound \(\hat{R}_{m,k}^{ub}[n]\) by

\[
(P3.1) : \max_{R_{fair}} \quad R_{fair}^{r}
\text{s.t.} \quad \frac{1}{N} \sum_{n=1}^{N} \sum_{m=1}^{M} \alpha_{m,k}[n] \left( -\hat{R}_{m,k}^{ub}[n] + \log_2 \left( \sum_{m'=1}^{M} p_{m'}[n] h_{m', k}[n] h_{m,k}[n] + \sigma^2 \right) \right)
\geq R_{fair}^{r}, \quad \forall k,
(9c), (9f).
\]

Now the constraint (28b) is convex. Furthermore, constraints (9c) and (9f) are all linear constraints. Therefore, problem (P3.1) is a convex optimization problem which can be efficiently solved by existing optimization tools such as CVX.

**C. BSN SCHEDULING OPTIMIZATION**

Given UAVs’ trajectories \(Q\) and UAV transmit power \(P\), the BSN scheduling \(A\) can be optimized by solving the following problem

\[
(P4) : \max_{R_{fair}} \quad R_{fair}
\text{s.t.} \quad (9b), (9c), (9g), (9h).
\]

Problem (P4) is a non-convex integer programming problem, and is difficult to be optimally solved in general. To tackle this problem, we relax the binary variables \(\{\alpha_{m,k}[n] \in \{0, 1\}, \forall k, m\}\) into continuous variables, and reformulate problem (P4) as

\[
(P4.1) : \max_{R_{fair}, A} \quad R_{fair}
\text{s.t.} \quad (9b), (9c), (9g), (9h),
0 \leq \alpha_{m,k}[n] \leq 1, \quad \forall k, m, n.
\]

Such a relaxation in general implies that the objective value of Problem (P4.1) serves as an upper bound for that of Problem (P4). Problem (P4.1) is a standard linear programming (LP) problem, and can be solved efficiently by existing optimization tools.

**D. ALGORITHM FOR JOINT OPTIMIZATION**

**Algorithm 1** Block coordinate descent algorithm for problem (P1).

1: Initialize \(Q^{(0)}, P^{(0)}\), and let \(r = 0\).
2: repeat
3: Solve problem (P4) for given \(\{Q^{(r)}, P^{(r)}\}\), and denote the optimal solution as \(A^{(r+1)}\).
4: Solve problem (P2.2) for given \(\{Q^{(r)}, P^{(r)}, A^{(r+1)}\}\), and denote the optimal solution as \(\{Q^{(r+1)}, P^{(r+1)}, A^{(r+1)}\}\).
5: Solve problem (P3.1) for given \(\{Q^{(r+1)}, P^{(r+1)}, A^{(r+1)}\}\), and denote the optimal solution as \(\{Q^{(r+1)}, P^{(r+1)}, A^{(r+1)}\}\).
6: Update \(r = r + 1\).
7: until The percentage increase of \(R_{fair}\) is below a threshold \(\epsilon > 0\).

Based on the solutions to the UAVs’ trajectories optimization sub-problem, the UAV transmit power optimization sub-problem and the BSN scheduling optimization sub-problem, we propose an iterative algorithm for problem (P1) by using the block coordinate descent method, as summarized in Algorithm 1. Since all the three sub-problems can be optimally solved, we may obtain an increasing \(R_{fair}\) in every iteration. By assuming that \(R_{fair}\) takes a finite value, Algorithm 1 is guaranteed to converge to a sub-optimum [35]. Since the computational complexity of every iteration is polynomial, the total complexity of the BCD aided iterative algorithm is also polynomial.

**E. RECONSTRUCT THE BINARY BSN SCHEDULING VARIABLES**

It is worth noting that, by relaxing the BSN scheduling which are binary variables into continuous variables, the relaxed problem, i.e., (P4.1), serves as an upper bound for that of the original problem, i.e., (P4), in general. If the BSN scheduling variables are all binary, then the relaxation is tight and the solution obtained by solving problem (P4.1) is also a feasible solution of problem (P4). Otherwise, we need to reconstruct the binary BSN scheduling variables based on the solution of problem

VOLUME 4, 2016
In particular, similar to the reconstruction process described in [10], in each iteration, we divide each time slot into τ sub-slots so that the new total number of sub-slots is $N' = τN$, $τ ≥ 1$. Then, the number of sub-slots assigned to BSN $k$ by UAV $m$ in time slot $n$ is $N_{m,k}[n] = τα_{m,k}[n]$, where $⌈x⌉$ denotes the nearest integer of $x$. It is not difficult to see that as $τ$ increases, $N_{m,k}[n]$ approaches an integer which allows a binary solution.

### IV. NUMERICAL RESULTS

In this section, we provide numerical simulation results to verify the performance of the designed multi-UAV assisted backscatter communication network. We consider a geographical area of size of $1 \times 1$ km$^2$ on the ground, where $K = 10$ BSNs are randomly and uniformly distributed. Other simulation parameters are set as listed in Table 1. It is worth noting that we adopt the trajectory initialization scheme for the multiple UAVs proposed in [10]. In particular, the initial trajectory of each UAV is set to be a circular trajectory with the UAV speed taking a constant value $V$, with $0 < V ≤ V_{\text{max}}$. Furthermore, the radius of the initial trajectory circles are assumed to be the same for all UAVs. And all circles together should cover the entire area as much as possible so as to better balance the rates.

#### A. SINGLE-UAV CASE

First, we focus on the special case of $M = 1$, where one single UAV is exploited to assist the BCN, to analyze the impact of the sequential energy constraint. In this case, there is no co-channel interference in the network, and it is not difficult to see that the UAV should always transmit with its maximum power, i.e., $p[n] = P_{\text{max}}, \forall n$.

To expose the impact of the sequential energy constraint, we compare two different energy initialization schemes for BSNs, i.e., two schemes with $E_0$ takes different values, with the other parameters set the same. In particular, the following two energy initialization schemes are considered: 1) The energy-full scheme, where $E_0$ is set to be 1 mJ, i.e., the BSNs have enough initial energy for circuit operating and signal backscattering, instead of relying on the energy harvesting, 2) The energy-hungry scheme, where $E_0$ is set to be 0 mJ, i.e., the BSNs are urgent to harvest energy from UAVs to maintain the circuit operation and support signal backscattering.

![Figure 2](image-url)  
(a) The optimized UAV trajectory with enough initial energy.  
(b) The optimized UAV trajectory with empty initial energy.

**Figure 2:** The optimized UAV trajectories with different energy initialization schemes.

In Figure 2, we compare the optimized UAV trajectory obtained by Algorithm 1 with two different energy initialization schemes. It can be observed from Figure 2(a) that, for the energy-full scheme, the UAV sequentially visits all the BSNs when the BSNs have enough initial energy. In contrast, for the energy-hungry scheme, each BSN has to gather energy before transmission since it has no initial energy. As shown in Figure 2(b), the UAV...
first flies along a path lies in the center of the region for better energy transferring, since most of the BSNs can harvest energy when the UAV stays in the center, and then it flies to reach the BSNs lied farther for better coverage and communication performance. Besides, it is worth to notice that, the BSNs lied in the margin of the area, e.g., BSN 2 and BSN 10, have not been visited by the UAV since the total flight period is fixed and limited. The brought performance degradation in communication can be viewed as a cost for the lack of initial energy at BSNs.

![Figure 4: Optimized UAV trajectories.](image)

**Figure 4: Optimized UAV trajectories.**

Next, we give the results of multi-UAV assisted harvest energy and backscatter carrier signals alternately. It is broken for the energy-hungry case since the BSNs has to gather energy for circuit operation while for BSNs are continuous for the energy-full case, while the scheduling algorithm in Figure 6 give a typical result of the optimized UA Vs’ backscatter communication network. Figure 4, Figure 5 and Figure 6 give a typical result of the optimized UA Vs’ trajectories, BSN scheduling and UAVs’ transmit power in one simulation with $M = 2$, respectively. First, from Figure 4 and Figure 5, it can be observed that, compared to the single UAV case, where one UAV flies around the whole region and provides wireless power transfer as well as communication service to all BSNs, in the multi-UAV case, the two UAVs cooperate to serve the BSNs. In particular, UAV 1 tends to serve the BSNs located in the left part of the region, and UAV 2 tends to cover the BSNs lied in the right part of the region.

Second, by Figure 6, it is observed that, the two UAVs balance obtaining higher communication rates and reducing interference by properly adjusting the transmit power. In particular, when the two UAVs are far away from each other, both of them tend to transmit with the maximum power so as to improve the spectrum efficiency, e.g., from $t = 10$ s to $t = 20$ s. In contrast, when the two UAVs are getting very close to each other, one UAV will reduce the transmit power to zero to avoid severe interference, e.g., from $t = 70$ s to $t = 90$ s, where the two UAVs are serving two nearby users located in the center. As such, strong direct links and weak co-channel interference can be achieved at the same time, which helps achieving a larger max-min rate.

![Figure 3: The optimized BSN scheduling with different energy initialization schemes.](image)

**Figure 3: The optimized BSN scheduling with different energy initialization schemes.**

Further, we compare the BSNs’ scheduling for the two cases, which are illustrated in Figure 3(a) and Figure 3(b), respectively. It can be observed that, compare to the energy-full case, for the energy-hungry case, the UAV has not activated any BSNs at the beginning of the flight, since the BSNs has to gather energy for circuit operation and signal backscattering first. Besides, the scheduling for BSNs are continuous for the energy-full case, while it is broken for the energy-hungry case since the BSNs harvest energy and backscatter carrier signals alternately.

**B. MULTI-UAV CASE**

Next, we give the results of multi-UAV assisted backscatter communication network. Figure 4, Figure 5 and Figure 6 give a typical result of the optimized UA Vs’ trajectories, BSN scheduling and UAVs’ transmit power...
transfer wireless power first, which reduces the time for communication. It is also worth to note that, for the proposed trajectory design, as the flight period $T$ increased, the gap between two energy initialization cases becomes small. In contrast, for the circular trajectory design, the gap is much larger, since the energy harvest performance of BSNs when the UAVs fly along cycles are not well.

V. CONCLUSION

In this paper, we have investigated a multi-UAV assisted backscatter communication network, where multiple UAVs are employed to transmit wireless power to as well as collect data from multiple backscatter sensor nodes deployed on the ground. We have innovatively formulated the joint optimization problem of trajectory and communication involving multiple UAVs to providing service for multiple backscatter sensor nodes, and have firstly considered the sequential energy constraints for BSNs. Then, the formulated optimization problem has been tackled by using the BCD method and SCA technique. Finally, the impact of the BSNs’ sequential energy constraint on the designed UAV trajectories has been analyzed and the performance of the proposed design has been verified by numerical results.

APPENDIX A PROOF OF LEMMA 1

To prove the convexity of function $f_m(x_1, \cdots, x_M)$ given by

$$f_m(x_1, \cdots, x_M) = \ln \left( \sum_{m' \neq m} \frac{c_1}{(x_{m'} + c_2)(x_m + c_2)} + \frac{c_1}{(x_m + c_2)^2} + c_3 \right),$$

we introduce two auxiliary functions $\xi(x, y)$ and $\psi(x)$, and first prove the convexity of the two auxiliary functions. In particular, $\xi(x, y)$ and $\psi(x)$ are respectively given by

$$\xi(x, y) = \ln \left( \frac{c_1}{(x + c_2)(y + c_2)} + c_3 \right),$$

$$\psi(x) = \ln \left( \frac{c_1}{(x + c_4)^2} + c_3 \right).$$
where $c_1, c_2, c_3$ and $c_4$ are given constants. For $\xi(x,y)$, its Hessian matrix is $\nabla^2 \xi(x,y) = \begin{bmatrix} \frac{\partial^2 \xi(x,y)}{\partial x^2} & \frac{\partial^2 \xi(x,y)}{\partial x \partial y} \\ \frac{\partial^2 \xi(x,y)}{\partial y \partial x} & \frac{\partial^2 \xi(x,y)}{\partial y^2} \end{bmatrix}$, with the second partial derivatives respectively given by

$$\frac{\partial^2 \xi(x,y)}{\partial x^2} = c_1 \left[ c_1 + 2c_3(x+c_2)(y+c_2) \right] (x+c_2)^2 [c_1+c_3(x+c_2)(y+c_2)]^2,$$

$$\frac{\partial^2 \xi(x,y)}{\partial y \partial x} = \frac{c_1 c_3}{x},$$

$$\frac{\partial^2 \xi(x,y)}{\partial y^2} = c_1 \left[ c_1 + 2c_3(x+c_2)(y+c_2) \right] (y+c_2)^2 [c_1+c_3(x+c_2)(y+c_2)]^2.$$

It can be proved that when $x > 0$ and $y > 0$, $t^2 \nabla^2 \xi(x,y)t \geq 0$ for any $t = [t_1, t_2]^T$. Therefore, $\xi(x,y)$ is jointly convex with respect to $x$ and $y$ for $x > 0$ and $y > 0$. Similarly, it can be proved that $\psi(x)$ is convex with respect to $x > 0$.

The function $f_m(x_1, \cdots, x_M)$ can be equivalently expressed as the composition of $\xi(x,y)$ and $\psi(x)$, given by

$$f_m(x_1, \cdots, x_M) = \ln \left( \sum_{m'=1}^{M} e^{\xi(x_m, x_m')} + e^{\psi(x_m)} \right).$$

According to [34], if $\xi(x,y)$ is convex with respect to $x$, $y$ for $x > 0$, $y > 0$, and $\psi(x)$ is convex with respect to $x$ for $x > 0$, then $f_m(x_1, \cdots, x_M)$ is jointly convex with respect to $x_1, \cdots, x_M$ for $x_1, \cdots, x_M \geq 0$.

References

[1] Y. C. Liang, Q. Zhang, E. G. Larsson, and G. Y. Li, “Symbiotic radio: Cognitive backscatter communications for future wireless networks,” IEEE Trans. Cognitive Commun. Netw., vol. 6, no. 4, Dec. 2020.

[2] W. Lu, S. Hu, X. Liu, C. He, and Y. Gong, “Incentive mechanism based cooperative spectrum sharing for OFDM cognitive IoT network,” IEEE Trans. Netw. Sci. Eng., vol. 7, no. 2, pp. 662-672, Apr. 2020.

[3] K. Han and K. Huang, “Wirelessly powered backscatter communication networks: modeling, coverage, and capacity,” IEEE Trans. Wireless Commun., vol. 16, no. 4, pp. 2548-2561, Apr. 2017.

[4] X. Lu, H. Jiang, D. Niyato, D. I. Kim, and Z. Han, “Wireless-powered device-to-device communications with ambient backscattering: Performance modeling and analysis,” IEEE Trans. Wireless Commun., vol. 17, no. 3, pp. 1528-1544, Mar. 2018.

[5] Y. Zhang, F. Gao, B. Li, and Z. Han, “A robust design for ultra-reliable ambient backscatter communication systems,” IEEE Internet Things J., vol. 6, no. 5, pp. 8989-8999, Oct. 2019.

[6] A. Bletsas, P. N. Alevizos, and G. Vougioukas, “The art of signal processing in backscatter radio for μw (or less) Internet of Things,” IEEE Signal Process. Mag., vol. 35, no. 5, pp. 28-40, Sep. 2018.

[7] G. Yang, X. Xu, and Y.-C. Liang, “Resource allocation in NOMA-enhanced backscatter communication networks for wireless powered IoT,” IEEE Wireless Commun. Lett., vol. 9, no. 1, pp. 117-120, Jan. 2020.

[8] I. Klimios, A. Bletsas and J. N. Sahalos, “Increased range bi-static scatter radio,” IEEE Trans. Commun., vol. 62, no. 3, pp. 1091-1104, March 2014.

[9] Y. Zeng, J. Lyu, and R. Zhang, “Cellular-connected UAV: Potential, challenges, and promising technologies,” IEEE Wireless Commun., vol. 26, no. 1, pp. 120-127, Feb. 2019.

[10] Q. Wu, Y. Zeng and R. Zhang, “Joint trajectory and communication design for multi-UAV enabled wireless networks,” IEEE Trans. Wireless Commun., vol. 17, no. 3, pp. 2109-2121, March 2018.

[11] L. Xie, J. Xu, and R. Zhang, “Throughput maximization for UAV-enabled wireless powered communication networks,” IEEE Internet of Things J., vol. 6, no. 2, pp. 1690-1703, Apr. 2019.

[12] 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.

[13] 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.

[14] W. Lu, T. Chen and X. Wang, “A Combinatorial Bandit Approach to UAV-aided Edge Computing,” 54th Asilomar Conference on Signals, Systems, and Computers, 2020, pp. 304-308.

[15] M. Hua, L. Yang, C. Li, Q. Wu, and A. L. Swindlehurst, “Throughput maximization for UAV-aided backscatter communication networks,” in IEEE Trans. Commun., vol. 68, no. 2, pp. 1254-1270, Feb. 2020.

[16] M. Hua, A. L. Swindlehurst, C. Li, and L. Yang, “UAV-aided backscatter networks: Joint UAV trajectory and protocol design,” Proc. IEEE Globecom, Waikoloa, HI, USA, 2020, pp. 1-6.

[17] S. Yang, Y. Deng, X. Tang, Y. Ding and J. Zhou, “Energy efficiency optimization for UAV-assisted backscatter communications,” IEEE Communications Letters, vol. 23, no. 11, pp. 2041-2045, 2019.

[18] G. Yang, R. Dai and Y. C. Liang, “Energy-efficient UAV backscatter communication with joint trajectory design and resource optimization,” IEEE Trans. Wireless Commun., vol. 20, no. 2, pp. 926-941, 2021.

[19] A. Farajzadeh, O. Erecit, and H. Yanikomeroglu, “UAV data collection over NOMA backscatter networks: UAV altitude and trajectory optimization,” Proc. IEEE ICC, Shanghai, China, May 2019, pp. 1-7.

[20] J. Hu, X. Cai and K. Yang, “Joint trajectory and scheduling design for UAV aided secure backscatter communications,” IEEE Wireless Communications Letters, vol. 9, no. 12, pp. 2168-2172, 2020.

[21] Q. Wu, Y. Zeng, and R. Zhang, “Joint trajectory and communication design for UAV-enabled multiple access,” Proc. IEEE Globecom, 2017.

[22] Y. Zeng, R. Zhang, and T. J. Lim, “Throughput maximization for UAV-enabled mobile relaying systems,” IEEE Trans. Commun., vol. 64, no. 12, pp. 4983-4996, Dec. 2016.

[23] 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.

[24] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, “Mobile unmanned aerial vehicles (UAVs) for energy-efficient internet of things communications,” IEEE Trans. Wireless Commun., vol. 16, no. 11, pp. 7574-7589, Nov. 2017.

[25] Y. Zeng, Z. Mou, F. Gao, L. Xing, J. Jiang and Z. Han, “Hierarchical deep reinforcement learning for backscattering data collection with multiple UAVs,” IEEE Internet Things J., vol. 8, no. 5, pp. 3786-3800, 1. 2021.

[26] D. W. Matolak and R. Sun, “Unmanned Aircraft Systems: Air-Ground Channel Characterization for Future Applications,” IEEE Veh. Technol. Mag., vol. 10, no. 2, pp. 79-85, June 2015.

[27] X. Kang, Y. C. Liang, and J. Yang, “Riding on the primary: A new spectrum sharing paradigm for wireless-powered IoT devices,” IEEE Trans. Wireless Commun., vol. 17, no. 9, pp. 6335-6347, Sep. 2018.

[28] G. Wang, F. Gao, R. Fan, and C. Tellambura, “Ambient backscatter communication systems: Detection and performance analysis,” IEEE Trans. Commun., vol. 64, no. 11, pp. 4836-4846, Nov. 2016.

[29] J. Qian, F. Gao, G. Wang, S. Jin, and H. Zhu, “Non-coherent detections for ambient backscatter system,” IEEE Trans. Wireless Commun., vol. 16, no. 3, pp. 1412-1422, Mar. 2017.
[30] Impinj, “M730 & M750 datasheet,” [Online]. Available: https://support.impinj.com/hc/en-us/articles/360010797539-Impinj-M730-M750-Product-Brief-Datasheet.

[31] B. Lyu, C. You, Z. Yang, and G. Gui, “The optimal control policy for RF-powered backscatter communication networks,” IEEE Trans. Veh. Technol., vol. 67, no. 3, pp. 2804–2808, Mar. 2018.

[32] P. Tseng, “Convergence of a block coordinate descent method for non-differentiable minimization,” J. Opt. Theory App., vol. 109, no. 3, pp. 475–494, Jun. 2001.

[33] A. Beck, A. Ben-Tal, and L. Tetruashvili, “A sequential parametric convex approximation method with applications to non-convex truss topology design problems,” J. of Global Opt., vol. 47, no. 1, pp. 29–51, May 2010.

[34] S. Boyd and L. Vandenberghe, “Convex Optimization: 7th Edition,” Cambridge University Press, 2009.

[35] D. P. Bertsekas, “Nonlinear Programming: 2nd Edition,” 1999.