

Sum Rate Optimization for UAV-assisted NOMA-based Backscatter Communication System

Zifu Fan[†], Yang Hu[†], Zhengqiang Wang^{†*}, Xiaoyu Wan[†], Bin Duo[‡]

[†] School of Communication and Information Engineering, Chongqing University of Posts and Telecommunications, Chongqing, China

[‡] College of Computer Science and Cyber Security, Chengdu University of Technology, Chengdu, China
fanzf@cqupt.edu.cn, S200101131@stu.cqupt.edu.cn, {wangzq,wanxy}@cqupt.edu.cn, duobin@cdut.edu.cn

Abstract—This paper considers a backscatter communication (BC) system, which is based on the non-orthogonal multiple access (NOMA) protocol and assisted by a full-duplex unmanned aerial vehicle (UAV). To improve the communication quality of this NOMA-based system, we increase the number of backscatter devices (BDs) and maximize the sum rate by optimizing the reflection coefficient (RC) of BDs and the location of the UAV. As the sum rate problem is a non-convex problem, we propose an iterative algorithm to solve the problem by using the block coordinated descent (BCD) technique and quadratic transform algorithm. The RC problem is solved by monotonicity. Then, the location problem is solved by the quadratic transform algorithm. Finally, simulation results demonstrate that the proposed algorithm achieves higher sum rate than the other schemes.

Index Terms—backscatter communication (BC), non-orthogonal multiple access (NOMA), unmanned aerial vehicle (UAV), sum rate, uplink.

I. INTRODUCTION

With the rapid development of mobile communication, throughput enhancement becomes a common concern. As a cost-effective communication technology, backscatter communication (BC) is suitable for large-scale and low-cost wireless devices with energy limitations. It also has a promising application in low-power wireless device communication. [1]. In BC, backscatter device (BD) is a passive device that reflects the incident radio frequency (RF) signal to transmit information without using complex and power-consuming active RF components, and also derives energy from the incident RF signal for its operation, thus significantly reducing circuit power consumption [2]. In daily life, BD can harvest energy for operation from ambient RF sources, such as cellular and television signals [3]. However, due to two-channel fades (the first from the transmitter to the BD and the second from the BD to the backscatter receiver (BR)), the final received signal is weak, resulting in low throughput, and the short distance from the BD to the BR, which makes BC range limited [4].

On the other hand, in wireless communication, UAV-assisted communication has attracted many researchers due to the ease of deployment, high mobility, and high probability of line-of-sight (LoS) links with ground users [5]. Meanwhile, non-orthogonal multiple access (NOMA) utilizes overlay coding at

the base station to transmit multiple user data simultaneously, and successive interference cancellation (SIC) at the receiver to decode the information, which can serve a large number of users at the same time [6]. In [7], the authors studied the performance of NOMA for UAV-assisted system. The results show that in most cases, the NOMA scheme performs much better than the orthogonal multiple access (OMA) scheme. Moreover, a NOMA-based BC system is investigated in [8]. The results show that NOMA has a great potential in BC. Therefore, the combination of BC, UAV, and NOMA can greatly improve the quality of communication.

In order to improve the capacity and reliability, the combination of BC and UAV have been extensively studied in [9] - [11]. In [9], the authors applied time division multiple access (TDMA) and divided the target region into multiple sub-regions to jointly optimize the time and reflection coefficient (RC) to maximize energy efficiency. In [10], the authors applied TDMA transmission scheme and proposed a communicate-while-fly scheme to maximize the system's energy efficiency by jointly optimizing the trajectory of the UAV, the scheduling of the BD, and the power of transmitter. The UAV's flight time was minimized in [11] by optimizing the UAV's altitude while maximizing the number of bits successfully transmitted in the uplink.

Different from the previous works in [9] and [10], we consider a full-duplex UAV which is used as a power transmitter and information receiver for BC system. Thus, we don't need additional base stations on land which can save resources. Furthermore, instead of using TDMA, we apply NOMA scheme to serve more backscatter devices (BDs). In addition, different from [11], we consider energy harvesting and residual self-interference (RSI) of UAV. Furthermore, we fix the height of UAV to analyse the impact of its position and RC of BD on the sum rate. After summarizing previous research and future communication trends, we study sum rate maximization for a BC system based on NOMA which is assisted by a full-duplex UAV. As the uplink sum rate maximization problem is a non-convex problem related to the RC and the UAV's position, which is difficult to handle. To solve this non-convex problem, we propose an iterative algorithm based on the block coordinated descent (BCD) technique and quadratic transform algorithm in this paper.

This paper has other four sections. Section II introduces the

*Corresponding author: Zhengqiang Wang(wangzq@cqupt.edu.cn)

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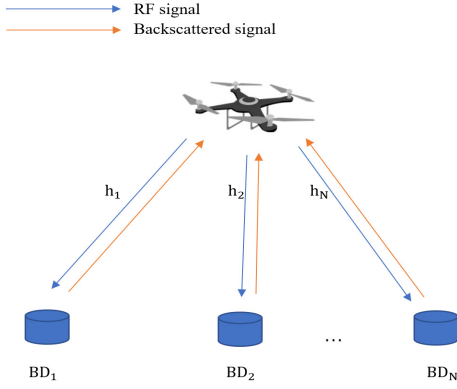


Fig. 1: UAV-assisted NOMA-based BC System

model of the proposed system and describes the optimization problem. Section III presents the joint optimization of the RC and the UAV's location. Section IV shows simulation results to illustrate the performance of our proposed algorithm. Finally, Section V concludes the paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

As shown in Fig.1, we consider an UAV-assisted backscatter network where N BDs are distributed independently in an area. The full-duplex UAV transmits RF signal to all the BDs in the downlink. Each BD uses its harvested energy from RF signal to send its information back to the UAV in the uplink. At the UAV, the effect of self-interference can't be fully eliminated. So, we consider the RSI of UAV and use SIC to decode the data of each BD. We assume that the UAV is fully aware of channel state information (CSI), and the available bandwidth is normalized. Denote all BDs by the set $\mathcal{N} \triangleq \{1, 2, \dots, N\}$. The location of UAV and j -th BD are given by (x_u, y_u, H) and (x_j, y_j) , where H is the fixed flight altitude of the UAV. We consider a free-space path loss model between BDs and UAV [12]. Therefore, the channel gain between BD j and UAV is given as $h_j = \frac{\beta_0}{d_j^2}$, where β_0 is the channel gain at the reference distance 1 m and $d_j = \sqrt{(x_u - x_j)^2 + (y_u - y_j)^2 + H^2}$ indicates the distance between UAV and BD j .

The transmitted signal from the UAV is $x(n)$ which satisfies $E[|x(n)|^2] = 1$. The integrated circuit at the BD only has passive components which do not have any active RF components, so the noise at the BD can be neglected [13]. Hence, the signal received by BD j from UAV is denoted by $\sqrt{h_j P_u} x(n)$, where P_u is the transmit power of UAV. The received signal is divided into two parts. The first part is denoted by $\sqrt{(1 - r_j) h_j P_u} x(n)$ which flies into BD j 's energy harvester. And the energy harvested by BD j is $E_j = \eta_j (1 - r_j) P_u h_j$ [14], where η_j and r_j denote energy conversion efficiency coefficient and the RC of BD j , respectively.

The second part is given as $\sqrt{r_j h_j P_u} x(n)$. The BD j modulates it and then backscatters the modulated signal to

the UAV. The signal backscattered by BD j is denoted by $\tilde{x}_j(n) = \sqrt{r_j h_j P_u} x(n) a_j(n)$, where $a_j(n)$ is BD j 's own signal satisfying $E[|a_j(n)|^2] = 1$.

Therefore, the signal received by the UAV is denoted by $y(n) = \sum_{j=1}^N \sqrt{h_j} \tilde{x}_j(n) + x_{uu} + n_0$, where x_{uu} denotes the RSI of UAV, i.e., $x_{uu} \sim CN(0, \alpha P_u |h_{uu}|^2)$ [15]. h_{uu} is the self-interference channel, i.e., $h_{uu} \sim CN(0, 1)$. $0 \leq \alpha \ll 1$ denotes the amount of RSI of UAV. $n_0 \sim CN(0, \sigma^2)$ denotes additive white Gaussian noise (AWGN) with variance σ^2 at UAV.

Without loss of generality, we assume that the decoding order is from BD 1 to BD N . Our objective is to maximize the sum rate of this system by optimizing the RC of BD and the location of UAV (x_u, y_u) . The j -th BD's rate can be denoted

$$R_j = \log_2 \left(1 + \frac{P_u r_j h_j^2}{\sum_{i=j+1}^N P_u r_i h_i^2 + \alpha P_u |h_{uu}|^2 + \sigma^2} \right).$$

Therefore, the sum rate of all the BDs is formulated by

$$R_{total} = \sum_{j=1}^N R_j = \log_2 \left(1 + \sum_{j=1}^N \frac{P_u r_j h_j^2}{\alpha P_u |h_{uu}|^2 + \sigma^2} \right) \quad (1)$$

The problem can be formulated as P1.

P1:

$$\begin{aligned} \max_{P_u, r_j, x_u, y_u} \quad & \log_2 \left(1 + \sum_{j=1}^N \frac{P_u r_j h_j^2}{\alpha P_u |h_{uu}|^2 + \sigma^2} \right) \\ \text{s.t.} \quad & \text{C1} : 0 \leq r_j \leq 1, \forall j \\ & \text{C2} : 0 \leq P_u \leq P_{max} \\ & \text{C3} : P_c \leq \eta_j (1 - r_j) P_u h_j, \forall j \end{aligned} \quad (2)$$

Constraint C1 means that the RC of BD is between 0 and 1. C2 constraints the maximum transmit power of the UAV. Constraint C3 shows the energy consumed by BD does not exceed the harvested energy [16], where P_c is the constant circuit power consumed by BD.

Obviously, the objective function and constraint C3 in P1 are non-convex. We propose an iterative algorithm as follows to solve it.

III. REFLECTION COEFFICIENT AND LOCATION OPTIMIZATION

In this part, we propose an iterative algorithm applying the BCD and quadratic transform [17] techniques. We optimize RC of BD and UAV's location to solve the problem.

A. Equivalent problem

Since $\sum_{j=1}^N \frac{P_u r_j h_j^2}{\alpha P_u |h_{uu}|^2 + \sigma^2} \geq 0$, P1 is equivalent to P2.

P2:

$$\begin{aligned} \max_{P_u, r_j, x_u, y_u} \quad & \sum_{j=1}^N \frac{P_u r_j h_j^2}{\alpha P_u |h_{uu}|^2 + \sigma^2} \\ \text{s.t.} \quad & \text{C1} : 0 \leq r_j \leq 1, \forall j \\ & \text{C2} : 0 \leq P_u \leq P_{max} \\ & \text{C3} : P_c \leq \eta_j (1 - r_j) P_u h_j, \forall j \end{aligned} \quad (3)$$

Obviously, for a fixed r_j and a fixed (x_u, y_u) , $\frac{P_u r_j h_j^2}{\alpha P_u |h_{uu}|^2 + \sigma^2}$ is an increasing function with respect to P_u . Combining constraint C2 and C3, we can get $\frac{P_c}{\eta_j(1-r_j)h_j} \leq P_u \leq P_{max}, \forall j$.

Hence, the optimal solution to P2 must satisfy $P_u = P_{max}$ and we take it to P2. Meanwhile, we also take the h_j into P2. Therefore, we can get the equivalent problem P3.

P3:

$$\begin{aligned} \max_{r_j, x_u, y_u} & \frac{P_{max} \sum_{j=1}^N \frac{r_j \beta_0^2}{[(x_u - x_j)^2 + (y_u - y_j)^2 + H^2]^2}}{\alpha P_{max} |h_{uu}|^2 + \sigma^2} \\ \text{s.t. C1} & : 0 \leq r_j \leq 1, \forall j \\ \text{C2} & : P_c \leq \frac{\eta_j(1-r_j)P_{max}\beta_0}{(x_u - x_j)^2 + (y_u - y_j)^2 + H^2}, \forall j \end{aligned} \quad (4)$$

The objective function and constraint C2 for variable r_j, x_u and y_u are both non-convex. Next we use BCD to handle it.

B. Reflection Coefficient Optimization

To solve this problem, we first fixed (x_u, y_u) . We can get problem P4.

P4:

$$\begin{aligned} \max_{r_j} & \frac{P_{max} \sum_{j=1}^N \frac{r_j \beta_0^2}{[(x_u - x_j)^2 + (y_u - y_j)^2 + H^2]^2}}{\alpha P_{max} |h_{uu}|^2 + \sigma^2} \\ \text{s.t. C1} & : 0 \leq r_j \leq 1, \forall j \\ \text{C2} & : P_c \leq \frac{\eta_j(1-r_j)P_{max}\beta_0}{(x_u - x_j)^2 + (y_u - y_j)^2 + H^2}, \forall j \end{aligned} \quad (5)$$

For simplicity, let $a = \frac{P_{max}}{\alpha P_{max} |h_{uu}|^2 + \sigma^2}$ to rewrite the objective function in P4. We can get $f(r_j) = \sum_{j=1}^N \frac{a \beta_0^2 r_j}{d_j^4}$.

Obviously, $f(r_j)$ is an increasing function with respect to r_j . The constraint C2 is equivalent to the following inequality:

$$r_j \leq 1 - \frac{P_c [(x_u - x_j)^2 + (y_u - y_j)^2 + H^2]}{\eta_j P_{max} \beta_0}, \forall j \quad (6)$$

In (6), r_j may be less than 0 as P_c increases. Therefore, P_c should have an upper bound to make the problem feasible. Obviously, P4 has a feasible solution when $P_c \leq \min\left(\frac{\eta_j P_{max} \beta_0}{H^2}\right), \forall j$.

Combining (6) with C1, we can get the close-form of the optimal RC

$$r_j^* = 1 - \frac{P_c [(x_u - x_j)^2 + (y_u - y_j)^2 + H^2]}{\eta_j P_{max} \beta_0}, \forall j \quad (7)$$

C. Location of UAV Optimization Algorithm

After fix the location of the UAV, we can get the optimal RC r_j^* . Then, we use it to optimize the location of the UAV. Substitute r_j^* into P3 to get P5.

P5:

$$\begin{aligned} \max_{x_u, y_u} & a \sum_{j=1}^N \frac{r_j \beta_0^2}{[(x_u - x_j)^2 + (y_u - y_j)^2 + H^2]^2} \\ \text{s.t. C1} & : (x_u - x_j)^2 + (y_u - y_j)^2 + H^2 \leq \frac{\eta_j(1-r_j)P_{max}\beta_0}{P_c}, \forall j \end{aligned} \quad (8)$$

P5 is non-convex because of its non-concave objective function, and it is also a non-linear fractional programming problem. Therefore, we adopt quadratic transform algorithm to solve it. Furthermore, we introduce Lemma 1 in [17].

Lemma 1: Given a non-empty constraint set $\chi \subseteq \mathbb{R}^d$, M pairs of nonnegative functions $\psi_m(x) : \mathbb{R}^d \rightarrow \mathbb{R}_+$, and M pairs of positive functions $\varpi_m(x) : \mathbb{R}^d \rightarrow \mathbb{R}_{++}$, where $m = 1, \dots, M, d \in \mathbb{N}$. Therefore, the sum-of-ratio problem can be denoted in this way:

$$\begin{aligned} \max_{\mathbf{x}} & \sum_{m=1}^M \frac{\psi_m(\mathbf{x})}{\varpi_m(\mathbf{x})} \\ \text{s.t.} & \mathbf{x} \in \chi \end{aligned} \quad (9)$$

(9) is equivalent to

$$\begin{aligned} \max_{\mathbf{x}, g} & \sum_{m=1}^M \left(2g_m \sqrt{\psi_m(\mathbf{x})} - g_m^2 \varpi_m(\mathbf{x}) \right) \\ \text{s.t.} & \mathbf{x} \in \chi, g_m \in \mathbb{R} \end{aligned} \quad (10)$$

where g_m represents a group of variables $\{g_1, \dots, g_M\}$.

According to Lemma 1, the problem P5 is equal to P6.

P6:

$$\begin{aligned} \max_{x_u, y_u, g_j} & \sum_{j=1}^N \left(2g_j \sqrt{\psi_j(x_u, y_u)} - g_j^2 \varpi_j(x_u, y_u) \right) \\ \text{s.t. C1} & : (x_u - x_j)^2 + (y_u - y_j)^2 + H^2 \leq \frac{\eta_j(1-r_j)P_{max}\beta_0}{P_c}, \forall j \end{aligned} \quad (11)$$

where $\psi_j(x_u, y_u) = r_j \beta_0^2$ and $\varpi_j(x_u, y_u) = [(x_u - x_j)^2 + (y_u - y_j)^2 + H^2]^2, \forall j$.

For a given g_j , the object function of P6 is a concave function with respect to x_u and y_u . Let $z_j = g_j^2 \geq 0, \forall j$. Thus, for a fixed z_j , P6 is equivalent to the convex optimization problem P7 and we propose Lemma 2.

P7:

$$\begin{aligned} \min_{x_u, y_u} & \sum_{j=1}^N z_j ((x_u - x_j)^2 + (y_u - y_j)^2) \\ \text{s.t. C1} & : (x_u - x_j)^2 + (y_u - y_j)^2 + H^2 \leq \frac{\eta_j(1-r_j)P_{max}\beta_0}{P_c}, \forall j \end{aligned} \quad (12)$$

Lemma 2: For a fixed $z_j \geq 0, \forall j$, the optimal solution of P7 is given as

$$x_u = \frac{\sum_{j=1}^N z_j x_j}{\sum_{j=1}^N z_j}, y_u = \frac{\sum_{j=1}^N z_j y_j}{\sum_{j=1}^N z_j}. \quad (13)$$

Proof : Let $h(x_u, y_u) = \sum_{j=1}^N z_j ((x_u - x_j)^2 + (y_u - y_j)^2)$, we get $\frac{\partial^2 h}{\partial x_u^2} = 2z_j \geq 0, \frac{\partial^2 h}{\partial y_u^2} = 2z_j \geq 0, \frac{\partial^2 h}{\partial x_u \partial y_u} = 0$. Hence, P7 is a convex optimization problem. The optimal solution (13) can be obtained by $\frac{\partial h}{\partial x_u} = 0, \frac{\partial h}{\partial y_u} = 0$.

According to Lemma 2 and [17], P6 can be solved by the Algorithm 1.

After getting the optimized location of the UAV by a fixed RC, we can update the RC r_j by substituting the obtained location into (7). Then, we can get a new location of

UAV (x_u, y_u) . To sum up, the location and RC are updated iteratively until convergence. Algorithm 2 shows the process of the algorithm.

Algorithm 1 Quadratic Transform Location Optimization Algorithm

Set the maximum iteration number l_{max} , the maximum tolerance ζ and $j \in \{1, \dots, N\}$.

Initialization: Let $x_u^0 = x_{ini}$, $y_u^0 = y_{ini}$;

compute $g_j^0 = \frac{\sqrt{r_j^0 \beta_0^2}}{[(x_u^0 - x_j)^2 + (y_u^0 - y_j)^2 + H^2]^2}$, $\forall j$;

compute $z_j^0 = (g_j^0)^2$, $\forall j$;

Set $l = 0$;

repeat

$l = l + 1$;

Update (x_u^l, y_u^l) :

$$x_u^l = \frac{\sum_{j=1}^N z_j^{l-1} x_j}{\sum_{j=1}^N z_j^{l-1}}, y_u^l = \frac{\sum_{j=1}^N z_j^{l-1} y_j}{\sum_{j=1}^N z_j^{l-1}} \text{ where } z_j^{l-1} = (g_j^{l-1})^2, \forall j;$$

Update $g_j^l = \frac{\sqrt{r_j^l \beta_0^2}}{[(x_u^l - x_j)^2 + (y_u^l - y_j)^2 + H^2]^2}$, $\forall j$;

until convergence

output The location of UAV is given by $x_u = x_u^l$ and $y_u = y_u^l$.

Algorithm 2 Reflection Coefficient and UAV's Location Optimization

Set the maximum iteration number l_{max} , the maximum tolerance ζ and $j \in \{1, \dots, N\}$.

Initialization Let $x_u^0 = x_{ini}$, $y_u^0 = y_{ini}$;

compute $r_j^0 = 1 - \frac{P_c [(x_u^0 - x_j)^2 + (y_u^0 - y_j)^2 + H^2]}{\eta_j P_{max} \beta_0}$, $\forall j$;

compute $g_j^0 = \frac{\sqrt{r_j^0 \beta_0^2}}{[(x_u^0 - x_j)^2 + (y_u^0 - y_j)^2 + H^2]^2}$, $\forall j$;

compute $z_j^0 = (g_j^0)^2$, $\forall j$;

Set $l = 0$;

repeat

$l = l + 1$;

Update (x_u^l, y_u^l) :

$$x_u^l = \frac{\sum_{j=1}^N z_j^{l-1} x_j}{\sum_{j=1}^N z_j^{l-1}}, y_u^l = \frac{\sum_{j=1}^N z_j^{l-1} y_j}{\sum_{j=1}^N z_j^{l-1}} \text{ where } z_j^{l-1} = (g_j^{l-1})^2, \forall j;$$

Update $r_j^l = 1 - \frac{P_c [(x_u^l - x_j)^2 + (y_u^l - y_j)^2 + H^2]}{\eta_j P_{max} \beta_0}$, $\forall j$;

Update $g_j^l = \frac{\sqrt{r_j^l \beta_0^2}}{[(x_u^l - x_j)^2 + (y_u^l - y_j)^2 + H^2]^2}$, $\forall j$;

until $|R_{total}(l+1) - R_{total}(l)| < \zeta$ or $l = l_{max}$

output The location of UAV is given by $x_u = x_u^l$ and $y_u = y_u^l$. The RC of BD is given by $r_j = r_j^l$, $\forall j$.

Then, we analyze the complexity of our proposed algorithm. We assume that the maximum iteration number of our proposed algorithm is L . Obviously, P6 is solved by the interior-point method. Since P6 has two variables and N constraints, the worst complexity is $O(N^{\frac{1}{2}} \log(\frac{1}{\zeta}))$ [18], where

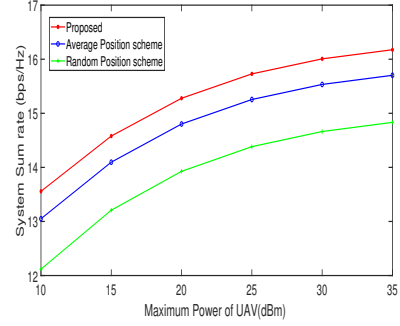


Fig. 2: System Sum Rate versus Maximum Power of UAV

ζ is the tolerance value. Thus, the complexity of our proposed algorithm is given as $O(LN^{\frac{1}{2}} \log(\frac{1}{\zeta}))$.

Finally, the convergence of Algorithm 2 is discussed as follows. Let $\mu(r^l, x_u^l, y_u^l)$ denote the value of the objective function in P3 in the l -th iteration and we have

$$\mu(r^l, x_u^l, y_u^l) \leq \mu_r(r^{l+1}, x_u^l, y_u^l) \quad (14)$$

where $\mu_r(r^{l+1}, x_u^l, y_u^l)$ is defined as the obtained objective value of P4 and r^{l+1} is the optimal solution to P4. For the optimization of the location (x_u, y_u) , we have

$$\mu(r^{l+1}, x_u^l, y_u^l) \leq \mu_{x_u, y_u}(r^{l+1}, x_u^{l+1}, y_u^{l+1}) \quad (15)$$

where μ_{x_u, y_u} is the objective value of P7 and (x_u^{l+1}, y_u^{l+1}) is the optimal solution to P7.

With (14)-(15), we can get

$$\mu(r^l, x_u^l, y_u^l) \leq \mu(r^{l+1}, x_u^{l+1}, y_u^{l+1}) \quad (16)$$

Therefore, Algorithm 2 ensures that the obtained objective value of P3 is non-decreasing over the iterations. Thus, it guarantees its convergence to the locally optimal solution to P3.

IV. SIMULATION RESULTS

In this section, simulation results are given to demonstrate the performance of the above iteration algorithm by optimizing the RC and location of the UAV. Without loss of generality, the simulation results are obtained by randomly generating BD positions and averaging 100 experiments. We set a BC system with one UAV and five BDs whose positions are randomly deployed in a 30m×30m square region. The other parameters as follow: $\beta_0 = 0.1$, $\eta = 0.6$, $P_c = 0.25\mu W$ [19], $\sigma^2 = -90$ dBm, and $\alpha = -100$ dB [15]. And our proposed scheme is compared with the other two schemes: average BD position scheme and random position scheme. In the average scheme, the RC is the optimized value in the proposed algorithm, UAV's location is the average of each BD's location which

$x_u = \frac{\sum_{j=1}^N x_j}{N}$ and $y_u = \frac{\sum_{j=1}^N y_j}{N}$. In the random scheme, the RC is the optimized value in the proposed algorithm. UAV's location x_u and y_u are both random values less than 30 m.

In Fig.2, the sum rate of three schemes increases as the power of the UAV goes from 10 dBm to 35 dBm where the

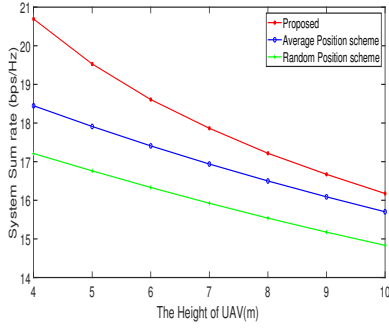


Fig. 3: System Sum Rate versus Height of UAV

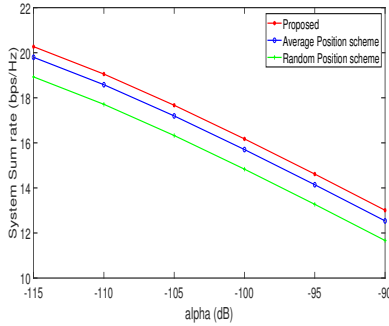


Fig. 4: System Sum Rate versus α

height of the UAV is set as 10 m. As the power of the UAV increases, the transmit power of BD also becomes larger and the sum rate increases. Among them, the proposed algorithm is better than the average scheme and the random scheme. When the maximum power of the UAV is 25 dBm, the proposed scheme is 3.1% and 9.4% higher than the sum rate obtained by the average scheme and the random scheme, respectively.

In Fig.3, as the height increases, the sum rate of the three schemes decreases simultaneously where the power of the UAV is 35 dBm. With the increasing of height, the path loss also becomes larger and the sum rate decreases. When the height is 5 m, the proposed scheme is 9.0% and 16.5% higher than the sum rate obtained by the average scheme and the random scheme, respectively.

In Fig.4, with the increasing of α , the sum rate of the three schemes decreases simultaneously where the height and power of the UAV are set as 10 m and 35 dBm, respectively. As the α increases, the influence of RSI also becomes more severe and the sum rate decreases. When α is -100 dB, the proposed scheme is 3.0% and 9.1% higher than the sum rate obtained by the average scheme and the random scheme, respectively.

V. CONCLUSION

In this paper, we have investigated the sum rate maximization problem for UAV-assisted NOMA-based BC System. We have solved this non-convex optimization problem by using the BCD technique and dividing it into RC optimization and UAV's location optimization. And we use monotonicity and quadratic transform algorithm to obtain the RC and UAV's

location, respectively. Simulation results have demonstrated that our proposed algorithm is superior to the other two benchmark schemes.

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