Abstract—In this letter, we study the resource allocation for an intelligent reflecting surface (IRS)-assisted uplink system, where the base station is equipped with multiple antennas. We propose to jointly optimize the transmit power of the users, active beamforming at the base station, and passive beamforming at the IRS to maximize the overall system energy efficiency while maintaining users’ minimum rate constraints. This problem belongs to a highly intractable non-convex bi-quadratic programming problem, for which an iterative solution based on block coordinate descent is proposed. Extensive simulations are conducted to demonstrate the effectiveness of the proposed scheme and the benefits of having more elements at the IRS.

Index Terms—Intelligent reflecting surface (IRS), multiple-input multiple-output (MIMO), resource allocation, uplink.

I. INTRODUCTION

INTELLIGENT reflecting surface (IRS) is a promising technology to boost the network performance for beyond 5G systems [1]–[4]. An IRS is an artificial passive radio planar array, which is composed of multiple low-cost reflecting elements. Each element can add a phase shift to the incident signal, forming various beam patterns. This way, the IRS is capable of tuning the wireless environment to support the data transmission.

So far, IRS has been applied to a variety of wireless networks [5]–[8]. For example, the IRS-aided multi-user multiple-input single-output (MISO) system has been considered in [5]–[8], requiring to optimize the active beamforming at the base station (BS) and passive beamforming at the IRS. More exactly, the authors in [5] consider the weighted sum rate maximization. Lagrangian dual transform is first employed to decouple the original problem. On this basis, the active and passive beamforming is optimized alternatively. The authors in [6] aim to maximize the minimum rate among users. The passive beamforming at the IRS is optimized when the channel between the BS and IRS is of rank-one and of full-rank, respectively. The authors in [7] study the total transmit power minimization subject to users’ individual minimum rate constraints. The beamforming for the single-user case is first addressed using alternating optimization, and on this basis, the multi-user case is addressed. The authors in [8] investigate the system energy efficiency (EE) maximization, and propose two computationally efficient beamforming solutions based on alternating maximization, gradient descent search, and sequential fractional programming. To further improve the performance, the IRS-aided MISO non-orthogonal multiple access (NOMA) system is studied in [9], where the objective is to maximize the EE for a two user system.

Note that all the above works [5]–[9] consider the downlink transmission. In this letter, we consider an IRS-assisted multi-antenna uplink system. To the best of our knowledge, [10] is the only work on IRS-based uplink system. However, [10] considers the sum rate maximization under a single-antenna BS. Considering the limited power supply at the user terminals, the EE maximization is of more relevance for uplink. Therefore, our goal is to maximize the system EE under users’ individual minimum rate requirements, involving a joint optimization of power control and beamforming design at both the BS and the IRS. An iterative solution based on block coordinate descent (BCD) is proposed to address the formulated highly intractable non-convex problem. Compared with existing works on EE maximization, i.e., [8], [9], the major differences lie in 1) we consider the active beamforming at the BS while [8] does not; 2) we consider the more general multi-user scenario while [9] only investigates the relatively simple two-user case. Finally, presented numerical results show the superiority of the proposed scheme over baselines that only optimize some of the three variables. Moreover, it is observed that having more IRS elements can yield better system performance improvement than having more BS antennas.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

As shown in Fig. 1, we consider an uplink system, where $K$ single-antenna users communicate with a multi-antenna BS. The number of antennas at the BS is $M$. Similar to [8], [9], it is assumed that no direct link exists between the users and BS due to unfavorable propagation conditions. Therefore, this communication takes place via an IRS with $N$ reflecting elements.
elements deployed on the facade of a building located in the proximity of both communication ends.

The signal received at the BS is given by

$$y = \sum_{k=1}^{K} G \Phi h_k \sqrt{P_k} s_k + n,$$

(1)

where $s_k$ denotes the signal from user $k$ and is of unit power, i.e., $E[|s_k|^2] = 1$, $k \in \{1, \ldots, K\}$, with $E$ being the expectation operation. $P_k$ is the corresponding transmit power of user $k$, satisfying $P_k \leq P_{k}^\text{max}$, with $P_{k}^\text{max}$ being the maximum transmit power. $h_k \in \mathbb{C}^{N \times 1}$ denotes the channel vector between user $k$ and IRS, while $G \in \mathbb{C}^{M \times N}$ represents the channel matrix between the IRS and BS. $\Phi = \text{diag}(\phi_1, \ldots, \phi_N)$ is an $N \times N$ diagonal matrix whose entries are the $N$ elements $\phi_1, \ldots, \phi_N$, with the $i$-th diagonal element $\phi_i$ satisfying $|\phi_i| = 1, \forall i \in \{1, \ldots, N\}$. The diagonal matrix $\Phi$ accounts for the effective phase shifts from all IRS reflecting elements. The constant modulus constraint $|\phi_i| = 1, \forall i \in \{1, \ldots, N\}$, is because the IRS simply reflects the received signal and cannot amplify it. $n \sim \mathcal{CN}(0, N_0 I_M)$ denotes the additive white Gaussian noise vector at the BS with power spectral density of $N_0$.

By applying the beamforming vector $v_k$ at the BS, we obtain

$$v_k^H y = v_k^H \sum_{i=1}^{K} G \Phi h_i \sqrt{P_i} s_i + v_k^H n$$

(2)

$$= v_k^H G \Phi h_k \sqrt{P_k} s_k + \sum_{i \neq k} v_k^H G \Phi h_i \sqrt{P_i} s_i + v_k^H n.$$

Accordingly, the signal-to-interference-plus-noise (SINR) of user $k$ can be expressed as

$$\gamma_k = \frac{|v_k^H G \Phi h_k|^2 P_k}{\sum_{i \neq k} |v_k^H G \Phi h_i|^2 P_i + |v_k^H n|^2},$$

(3)

and the achievable data rate of user $k$ is given by $R_k = \log_2(1 + \gamma_k)$.

B. Problem Formulation

In this letter, we aim to maximize the system EE under users’ quality-of-service (QoS) constraints. The considered problem can be formulated as follows:

$$\max_{P, V, \Phi} \frac{\sum_{k=1}^{K} \log_2(1 + \gamma_k)}{\psi \sum_{k=1}^{K} P_k + P_c},$$

(4a)

s.t.

$$\gamma_k \geq \gamma_k^{\text{min}}, \quad \forall k \in \{1, \ldots, K\}$$

(4b)

$$P_k \leq P_k^{\text{max}}, \quad \forall k \in \{1, \ldots, K\}$$

(4c)

$$|\phi_i| = 1, \quad \forall i \in \{1, \ldots, N\},$$

(4d)

where $P = [P_1, \ldots, P_K]$ and $V = [v_1, \ldots, v_K]$ are the transmit power vector and the receiver beamforming matrix, respectively. $\psi$ is a constant accounting for the power amplifier inefficiency. $P_c$ denotes the fixed circuit power consumption of all the users [11].

III. PROPOSED SOLUTION

One can show that the problem in (4) is non-convex and it requires the joint optimization of the passive beamforming at the IRS, active beamforming at the BS, and power control at the users. In particular, the main difficulty in solving (4) lies in the coupling among the optimization variables. To address this difficulty, we adopt BCD to decompose the problem into three subproblems of $P$, $V$ and $\Phi$, and solve them alternatively.

A. Power Control at the Users

Under given $V$ and $\Phi$, the power control problem can be simplified as

$$\max_P \sum_{k=1}^{K} \log_2(1 + \gamma_k)$$

(5a)

$$\psi \sum_{k=1}^{K} P_k + P_c$$

s.t.

$$\gamma_k \geq \gamma_k^{\text{min}}, \quad \forall k \in \{1, \ldots, K\}$$

(5b)

$$P_k \leq P_k^{\text{max}}, \quad \forall k \in \{1, \ldots, K\}.$$ (5c)

It is clear that (5) is a fractional problem, which can be transformed into a series of parametric sub-problems as follows:

$$\max_P \sum_{k=1}^{K} \log_2(1 + \gamma_k) - \lambda^{(l-1)} \left( \psi \sum_{k=1}^{K} P_k + P_c \right)$$

(6a)

s.t.

$$\gamma_k \geq \gamma_k^{\text{min}}, \quad \forall k \in \{1, \ldots, K\}$$

(6b)

where $l$ is the iteration index and $\lambda^{(l-1)}$ is a non-negative parameter. Starting from $\lambda^{(0)} = 0$, $\lambda^{(l)}$ can be updated as

$$\lambda^{(l)} = \frac{\sum_{k=1}^{K} \log_2(1 + \gamma_k^{(l)})}{\psi \sum_{k=1}^{K} P_k^{(l)} + P_c},$$

where $\gamma_k^{(l)}$ and $P_k^{(l)}$ are the updated SINRs and power after solving (6). Moreover, the maximum value of (6) is calculated as $\varepsilon^{(l)} = \sum_{k=1}^{K} \log_2(1 + \gamma_k^{(l)}) - \lambda^{(l-1)} \left( \psi \sum_{k=1}^{K} P_k^{(l)} + P_c \right)$. As shown in [12], $\lambda^{(l)}$ keeps growing while $\varepsilon^{(l)}$ keeps declining as $l$ increases. When $\varepsilon^{(l)} = 0$, $\lambda^{(l)}$ is maximized, which is also the maximum EE of (5).

The problem now lies in how to solve (6) for a given $\lambda$. It is clear that (6) is a non-convex optimization problem due to the non-concave objective function. Let us denote $g_{k,i} = \frac{|v_k^H G \Phi h_i|^2}{\sqrt{v_k^H n}}$ to simplify the used notation. After a straightforward mathematical manipulation, the objective function in (6) can be re-written as

$$f = \frac{\sum_{k=1}^{K} \log_2 \left( \sum_{i=1}^{K} P_i g_{k,i} + 1 \right) - \lambda \left( \psi \sum_{k=1}^{K} P_k + P_c \right)}{f_1(P)}$$

where $f_1(P)$
and the QoS constraints in (6b) can be reformulated as
\[ P_k g_{k,k} \geq \gamma_k^\text{min} \left( \sum_{i \neq k} P_i g_{k,i} + 1 \right), \quad \forall k \in \{1, \ldots, K\}, \] (8)
which is an affine constraint. Then, the power control optimization problem can be rewritten as
\[ \max \quad f_1(P) - f_2(P), \quad \text{s.t.} \quad (8), (5c), \] (9)
where both functions \( f_1(P) \) and \( f_2(P) \) are concave functions. Thus, the objective \( f_1(P) - f_2(P) \) is a DC function (difference of two concave functions). For \( k \in \{1, \ldots, K\} \), the vector \( e_k \in \mathbb{R}^K \) satisfying \( e_k(k) = 0 \) and \( e_k(i) = \frac{g_{k,i}}{\max_i g_{k,i}} \), \( i \neq k \). The gradient of \( f_2(P) \) is given by [13]
\[ \nabla f_2(P) = \sum_{k=1}^{K} \frac{e_k}{1 + \sum_{i \neq k} g_{k,i} P_i}. \] (10)

The following procedure generates a sequence \( \{P^{(l)}\} \) of improved feasible solutions. Initialized from a feasible \( \{P^{(0)}\} \), \( \{P^{(l)}\} \) is obtained as the optimal solution of the following convex problem at the \( l \)-th iteration [13]:
\[ \max \quad f_1(P) - f_2(P^{(l-1)}) - \langle \nabla f_2(P^{(l-1)}), P - P^{(l-1)} \rangle \]
\[ \text{s.t.} \quad (8), (5c), \] (11)
where \( \langle \cdot, \cdot \rangle \) denotes the inner product operation. Note that (11) can be efficiently solved by available convex software packages [14].

### B. Active Beamforming at the BS

Under given \( \Phi \) and \( P \), it can be seen that the SINR of user \( k \) only depends on \( v_k \) according to (2). For notational simplicity, denote \( \hat{h}_k = G \Phi h_k \). The optimal beamforming vector which can balance the interference and noise is given by
\[ v_k = \left( N_0 I_N + \sum_{i \neq k} P_i \hat{h}_i \hat{h}_i^H \right)^{-1} \hat{h}_k, \] (12)
and is referred to as the minimum mean square error (MMSE) receiver [15]. The corresponding output SINR in this case is given as
\[ \gamma_k = P_k \hat{h}_k^H \left( N_0 I_N + \sum_{i \neq k} P_i \hat{h}_i \hat{h}_i^H \right)^{-1} \hat{h}_k. \]

### C. Passive Beamforming at the IRS

Under given \( V \) and \( P \), the beamforming optimization at the IRS can be simplified as
\[ \max_{\Phi} \quad \sum_{k=1}^{K} \log_2 (1 + \gamma_k) \]
\[ \text{s.t.} \quad \gamma_k \geq \gamma_k^\text{min}, \quad \forall k \in \{1, \ldots, K\} \]
\[ |\phi_i| = 1, \quad \forall i \in \{1, \ldots, N\}. \] (13a, 13b, 13c)

To easily handle the term \( |v_k^H G \Phi h_i|^2 \) that appears in the SINR expression, we first re-arrange the diagonal matrix \( \Phi \) into a vector \( w \in \mathbb{C}^{N \times 1} \), with element \( w_j = \phi_j^H, \forall j \in \{1, \ldots, N\} \). It is clear that \( w \) contains all the information of \( \Phi \). Then, we introduce an auxiliary vector \( \tilde{h}_{k,i} = (v_k^H G) \circ h_i \), where the operation \( \circ \) represents the Hadamard product. Accordingly, it can be easily verified that the following equality holds
\[ |v_k^H G \Phi h_i|^2 = |w^H \tilde{h}_{k,i}|^2. \] Then, problem (13) can be re-expressed as
\[ \max_w \quad \sum_{k=1}^{K} \log_2 \left( 1 + \frac{|w^H \tilde{h}_{k,k}|^2 P_k}{\sum_{i \neq k} |w^H \tilde{h}_{k,i}|^2 P_i + \sigma_k^2} \right) \]
\[ \text{s.t.} \quad |w^H \tilde{h}_{k,k}|^2 P_k \geq \gamma_k^\text{min} \sum_{i \neq k} |w^H \tilde{h}_{k,i}|^2 P_i + \sigma_k^2, \quad \forall k, \]
\[ |w_j| = 1, \quad \forall i \in \{1, \ldots, N\}, \] (14a, 14b)
where \( \sigma_k^2 = |v_k^H w|^2 \). To address (14), we further reformulate
\[ |w^H \tilde{h}_{k,i}|^2 P_i = w^H P_i \tilde{h}_{k,i} \tilde{h}_{k,i}^H w = \text{Tr}(w^H P_i \tilde{h}_{k,i} \tilde{h}_{k,i}^H w) = \text{Tr}(P_i \tilde{h}_{k,i} \tilde{h}_{k,i}^H w w^H). \] (15)

Now, we introduce two auxiliary matrices \( H_{k,i} = P_i \tilde{h}_{k,i} \tilde{h}_{k,i}^H \) and \( W = w w^H \). It can be easily verified that \( H_{k,i} \) and \( W \) are positive semi-definite matrices. Meanwhile, problem (14) can be re-expressed as
\[ \max_w \quad \sum_{k=1}^{K} \log_2 \left( 1 + \frac{\text{Tr}(WH_{k,k})}{\sum_{i \neq k} \text{Tr}(WH_{k,i}) + \sigma_k^2} \right) \]
\[ \text{s.t.} \quad \text{Tr}(WH_{k,k}) \geq \gamma_k^\text{min} \sum_{i \neq k} \text{Tr}(WH_{k,i}) + \sigma_k^2, \quad \forall k \] (16a, 16b)
\[ \text{diag}(W) = 1, \quad W \succeq 0, \] (16c, 16d)
\[ \text{rank}(W) = 1, \] (16e)
where \( \text{diag}(W) \) returns the diagonal elements of \( W \). Thus, \( \text{diag}(W) = 1 \) is equivalent to \( w_i^2 = 1 \), and further \( |w_j| = 1, \forall i \in \{1, \ldots, N\} \).

Problem (16) is still non-convex due to the non-convex objective function (16a) and the rank one constraint (16c). The rank one constraint (16e) can be replaced with a convex positive semidefinite constraint \( W = w w^H \succeq 0 \), where \( w \in \mathbb{C}^{N \times 1} \) is an auxiliary variable. Further, \( W = w w^H \succeq 0 \) can be replaced with its convex Schur complement as follows:
\[ \begin{pmatrix} W & w \\ w^H & 1 \end{pmatrix} \succeq 0. \] (17)

Now, let us study the objective function (16a), which can be re-expressed as (18) at the bottom of the next page. It can be seen that (18) is a DC function, and thus, can be handled using DC programming. However, we cannot simply use the partial derivative for real variables as in (10) since \( W \) is a complex matrix. Moreover, the real function \( f_3(W) \) is not complex-analytic (holomorphic), and thus, its derivative with respect to \( W \) does not exist in the conventional sense of a complex derivative [16]. To address this issue, we need to calculate the derivatives of \( f_3 \) over both the real and imaginary parts of \( W \). According to the symmetry of \( W \) and \( \text{diag}(W) = 1 \), we only need to calculate the real and
imaginary parts of the elements below the diagonal of $W$. For $W(n,j), \forall n \in \{1, \ldots, N\}, j < n$, we have

$$\frac{\partial f_4}{\partial \Re(W(n,j))} = \ln 2 \sum_{k=1}^{K} \frac{\text{Tr}(W\sum_{i \neq k} H_{k,i}^H(n,j) + \sigma_k^2)}{\sum_{i \neq k} \text{Tr}(WH_{k,i}^H(n,j)) + \sigma_k^2},$$

$$\frac{\partial f_4}{\partial \Im(W(n,j))} = -\ln 2 \sum_{k=1}^{K} \frac{\text{Tr}(W\sum_{i \neq k} H_{k,i}^H(n,j) - \sigma_k^2)}{\sum_{i \neq k} \text{Tr}(WH_{k,i}^H(n,j)) + \sigma_k^2},$$

where $\Re(\cdot)$ and $\Im(\cdot)$ are the operations of obtaining the real and imaginary parts of a complex variable, respectively. Additionally, $W(n,j)$ and $H_{k,i}(n,j)$ denote the $(n,j)$-th element of $W$ and $H_{k,i}$, respectively.

Then, at the $l$-th iteration of the DC programming, problem (16) can be re-written as (19) at the bottom of the page. It is clear that (19) is a semidefinite programming (SDP), and is convex. Therefore, the optimal solution can be obtained using standard convex optimization methods, such as the interior-point method with a complexity of $O((K + N^2)^{3.5})$. Now the question becomes how to convert the global solution $W^*$ and $\bar{w}^*$ of (19) (after dropping rank one constraint) to a feasible solution of the original problem (16) (that has a rank one constraint). We use Gaussian randomization to address this issue, where the solution is considered as the mean of a multivariate Gaussian random vector with $W^* - \bar{w}^*W^H\sigma^2$ as its covariance matrix. In particular, we generate $Q$ trials of a random variable $\tilde{e}_{q} \sim N(w^*, W^* - \bar{w}^*W^H\sigma^2)$, $q = 1, \ldots, Q$. Since $\tilde{e}_{q}$ is not guaranteed to be feasible, we apply a rescaling factor to obtain the feasible candidate solution vector $\tilde{w}_{fq}, \ldots, \tilde{w}_{fQ}$. Assume $\tilde{w}_{f\bar{q}}$ is the one which maximizes the objective. We need to compare it with the previous $\tilde{w}$, and then, select the better one. We note that the above proposed solution can be applied to the downlink scenario as well.

D. Iterative Update Until Convergence

The EE is maximized after we repeat the following steps until convergence: 1) solve (11) iteratively to find $P$; 2) calculate $V$ using (12); and 3) solve (19) iteratively and use Gaussian randomization to find $\Phi$. Note that convergence is guaranteed since the EE increases or remains unchanged at each iteration and the EE clearly has an upper bound.

$$\sum_{k=1}^{K} \log_2 \left(1 + \frac{\text{Tr}(WH_{k,k})}{\sum_{i \neq k} \text{Tr}(WH_{k,i}^H) + \sigma_k^2}\right) = \sum_{k=1}^{K} \log_2 \left(\sum_{i=1}^{K} \text{Tr}(WH_{k,i}^H) + \sigma_k^2\right) - \sum_{k=1}^{K} \log_2 \left(\sum_{i \neq k} \text{Tr}(WH_{k,i}^H) + \sigma_k^2\right)$$

IV. SIMULATION RESULTS

In this section, simulations are conducted to verify the effectiveness of the proposed solution. The default simulation parameters are set as follows [5], [7]: the IRS is composed of 4 elements, while the BS is equipped with 4 antennas. Additionally, the number of users is 3. The distance between the BS and IRS and that between the IRS and users are generated randomly with a uniform distribution within 50 and 100 m, respectively. The small-scale fading between the BS and IRS and that between the IRS and users are modeled by the Rician (K-factor is 5) and Rayleigh fading, respectively. Meanwhile, the corresponding large-scale path-loss of these two channels follows $30 + 24 \log_{10}(d) + 30 + 28 \log_{10}(d)$, respectively, where $d$ is the distance in meters. The bandwidth is $B = 1$ MHz, while the noise power spectral density is $N_0 = -174$ dBm/Hz. Additionally, the fixed power consumption $P_e$ is 50 mW, while the power inefficiency $\psi$ is $1/3.5$. For simplicity, we assign the same maximum transmit power and minimum rate requirement to all users.

We consider the following baseline schemes: 1) jointly optimize $P$ and $V$ under fixed $\Phi$, referred to as “Fix IRS”; 2) jointly optimize $P$ and $\Phi$ under fixed $V$, referred to as “Fix BS”; 3) jointly optimize $V$ and $\Phi$ under fixed $P$, referred to as “Fix PA”; and 4) randomly set the values for all the variables, referred to as “Fix all”.

Figure 2 compares the proposed scheme with the baseline ones as the maximum transmit power increases. Clearly, the proposed scheme, i.e., “Prop” is the best, while “Fix all” is the worst. This shows that joint resource allocation can better balance users’ channel quality, inter-user interference and noise effect, and thus, lead to improved EE. Meanwhile, the EE for “Prop”, “Fix IRS” and “Fix BS” first grows with the maximum transmit power, and then saturates. This can be explained by the concavity of the log function for the rate, which results in some power unused in order to maximize the EE under high maximum transmit power. In contrast, when the power is not controlled properly, e.g., in “Fix PA” and “Fix all”, increasing the maximum transmit power may lead to a decrease in EE.

Figure 3 plots the EE versus the number of reflecting elements at the IRS for all schemes. It is clear that the EE for all schemes increases with the number of reflecting elements at
seen that having more elements at the IRS can lead to higher EE improvement than having more antennas at the BS. This is probably because the IRS elements affect both the channel between the BS and the IRS and that between the IRS and the users. In contrast, the antenna at the BS only affects the channel between the BS and the IRS.

V. CONCLUSION

In this letter, we studied the EE maximization for a multi-user multi-antenna uplink system with the aid of IRS. Three different variables, namely the transmit power at the users, phase shift at the IRS and beamforming matrix at the BS need to be jointly optimized. An iterative solution based on block coordinate descent was proposed, which handles one variable at one iteration. Numerical results showed that the proposed scheme dominates the baselines that optimize only some of the variables. Results also indicated that increasing the number of IRS elements leads to better improvements of the system EE when compared to increasing the number of antennas the BS.

REFERENCES

[1] E. Basar, M. Di Renzo, J. De Rosny, M. Debbah, M.-S. Alouini, and R. Zhang, “Wireless communications through reconfigurable intelligent surfaces,” IEEE Access, vol. 7, pp. 116753–116773, 2019.
[2] S. Gong et al., “Toward smart wireless communications via intelligent reflecting surfaces: A contemporary survey,” IEEE Commun. Surveys Tuts., vol. 22, no. 4, pp. 2283–2314, 4th Quart., 2020.
[3] J. Zhao, “A survey of intelligent reflecting surfaces (IRSs): Towards 6G wireless communication networks,” 2019. [Online]. Available: arXiv:1907.04789.
[4] Q. Wu and R. Zhang, “Towards smart and reconfigurable environment: Intelligent reflecting surface aided wireless network,” IEEE Commun. Mag., vol. 58, no. 1, pp. 106–112, Jan. 2020.
[5] H. Guo, Y.-C. Liang, J. Chen, and E. G. Larsson, “Weighted sum-rate maximization for reconfigurable intelligent surface aided wireless networks,” IEEE Trans. Wireless Commun., vol. 19, no. 5, pp. 3064–3076, May 2020.
[6] Q.-U.-A. Nadeem, A. Kammoun, A. Debbah, M. Debbah, and M.-S. Alouini, “Asymptotic max–min SINR analysis of reconfigurable intelligent surface assisted MISO systems,” IEEE Trans. Wireless Commun., vol. 19, no. 12, pp. 7748–7764, Dec. 2020.
[7] Q. Wu and R. Zhang, “Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming,” IEEE Trans. Wireless Commun., vol. 18, no. 11, pp. 5394–5409, Nov. 2019.
[8] C. Huang, A. Zappone, G. C. Alexandropoulos, M. Debbah, and C. Yuen “Reconfigurable intelligent surfaces for energy efficiency in wireless communication,” IEEE Trans. Wireless Commun., vol. 18, no. 8, pp. 4157–4170, Aug. 2019.
[9] F. Fang, Y. Xu, Q. V. Pham, and Z. Ding, “Energy-efficient design of IRS-NOMA networks,” IEEE Trans. Veh. Technol., vol. 69, no. 11, pp. 14088–14092, Nov. 2020.
[10] M. Zeng, X. Li, G. Li, W. Hao, and O. A. Dobre, “Sum rate maximization for IRS-assisted uplink NOMA,” IEEE Commun. Lett., vol. 25, no. 1, pp. 234–238, Jan. 2021.
[11] M. Zeng, W. Hao, O. A. Dobre, and H. V. Poor, “Energy-efficient power allocation in uplink mmWave massive MIMO with NOMA,” IEEE Trans. Veh. Technol., vol. 68, no. 3, pp. 3000–3004, Mar. 2019.
[12] W. Dinkelbach, “On nonlinear fractional programming,” Manag. Sci., vol. 13, no. 7, pp. 492–498, Mar. 1967.
[13] H. H. Kha, H. D. Thuan, and H. H. Nguyen, “Fast global optimal power allocation in wireless networks by local D.C. programming,” IEEE Trans. Wireless Commun., vol. 11, no. 2, pp. 510–515, Feb. 2012.
[14] M. Grant and S. Boyd. (Dec. 2010). CVX: MATLAB Software for Disciplined Convex Programming, Version 1.21. [Online]. Available: http://cvxr.com/cvx
[15] D. Tse and P. Viswanath, Fundamentals of Wireless Communication. Cambridge, U.K.: Cambridge Univ. Press, 2005.
[16] K. Kreutz-Delgado, “The complex gradient operator and the CR-calculus,” 2009. [Online]. Available: arXiv:0906.4835.