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Multi-Device Rate Maximization for IRS-Based Smart Home

Yanchen Wang and Yejun He*
State Key Laboratory of Radio Frequency Heterogeneous Integration
Guangdong Provincial Engineering Research Center of Base Station Antennas and Propagation
Shenzhen Key Laboratory of Antennas and Propagation
College of Electronics and Information Engineering, Shenzhen University, 518000, China
Email: w15690867106@163.com, heyejun@126.com*

***Abstract*—Intelligent reflecting surface (IRS) consisting of a plane including many passive components can control event signals and create a programmable wireless environment by reconfigurable passive components. Passive components are typically composed of electronic components such as positive intrinsic-negative (PIN) diodes, field effect transistors, and micro electromechanical system switches, whose inherent characteristics show without active circuitry. Given that intelligent reflecting surfaces can strengthen the property of wireless transmission channels by adjusting the phase of incident signals, we investigate a multi-input single-output smart home model for downlink multi-users in this paper. An alternating optimization (AO) algorithm is proposed to cope with the challenge of maximizing the weighted sum of objectives of multiple users. To increase the sum rate, the beamforming vector at the access point and the phase shift matrix at the IRS are jointly tuned. In perfect channel state information, the AO approach is employed to achieve the effect of user maximization. Typically, fractional programming is utilized to optimize the beamforming vector at AP, while the Riemannian conjugate gradient approach is used to design the phase shift at IRS. Compared with the baseline methods, our proposed method can significantly improve convergence of the system.**

***Index Terms*—Intelligent reflecting surface, smart home, multiple-input single-output (MISO), fractional programming, Riemannian conjugated gradient.**

I. Introduction

Intelligent reflecting surface (IRS) is a highly promising technology that has garnered widespread attention from the academic and industrial communities due to its significant potential for development. IRS is a flat surface integrated by a lot of passive components, which were implemented by diodes to achieve tunable phase shift, thus enabling different phase changes of IRS components [1]. Despite the adaptability of 5G physical layer technology to changing wireless environments in terms of space and time, the signal propagation is inherently stochastic and subject to unpredictable variations. By dynamically manipulating phase adjustment of reflective elements at IRS, it is possible to synergistically combine reflected signals with other propagation paths to amplify power of the received signals at the intended receivers, or to differentially interfere with signals at unintended receivers for interference suppression and improved security/privacy, as noted in [2]. Additionally, in scenarios where the direct link channel is obstructed by obstacles, the signal reflected from the IRS

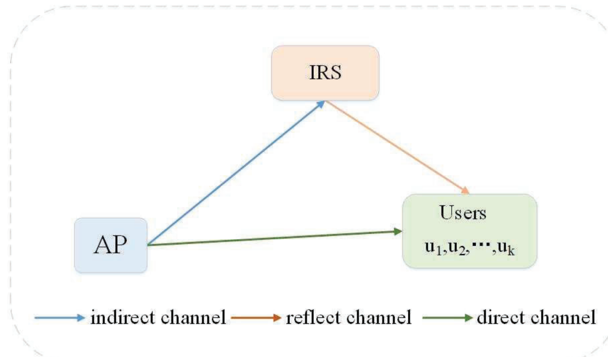

Fig. 1. An IRS-based multiuser system.

can be constructively combined with direct signal resulting in signal enhancement. In application scenario of smart home, the presence of walls and other barriers may weaken or block signals. In order to enhance the signal strength, the IRS is used in rooms. Specifically, the signal transmitted by the home gateway is reflected by the IRS, bypasses obstacles, and then constructively adds the direct link signal to achieve the effect of signal enhancement. Besides, the IRS is also commonly acknowledged as large intelligent surface (LIS) [3], large intelligent metasurface (LIM) [4], reconfigurable intelligent surface (RIS) [5], and so on. Actually, these concepts appeared in current articles are the same as the IRS.

Since obtaining accurate channel state information (CSI) in the system is challenging [6], we take the ideal CSI knowledge into consideration. Furthermore, it is crucial to think about robust transmission strategies for IRS-enabled wireless systems. To achieve the optimal multi-user performance in the case of perfect CSI, the majorization of transmit beamforming vector at access point (AP) and the phase shift matrix at IRS should be jointly conducted. Typically, the alternating optimization (AO) approach is employed to address this majorization issue. In [7], efficient algorithm of alternating optimization was utilized for solving the joint beam optimization issue. By fixing one variable to optimize another variable, the difficulty of calculation is greatly reduced. In order to achieve the maximum minimum signal-to-interference-plus-noise ratio

(SINR) among every user, AO algorithm was utilized to solve the joint collaborative reflection and receiving beamforming optimization problem, which introduces both individual user and multiple user situations in [8]. And single user without interference between the users utilizes the AO algorithm for cooperative passive beamforming design, and multi-user AO algorithm adopts the positive semidefinite relaxation (SDR) and bisection. The relationship between the loss of the line of sight path of RIS-assisted wireless communication with free space propagation and the distance from the TX/RX to RIS, the physical magnitude of RIS, the near-zone/far-zone effect of RIS, as well as the radiation pattern of antennas and elements were revealed [9]. In the context of optimizing achievable rates for multiple-in multiple-out (MIMO) systems, [10] presented an iterative optimization (IO) methodology utilitizing the projected gradient method (PGM). Notably, maximum ratio combining receivers tend to exhibit inferior performance compared to zero-forcing and minimum mean squared error receivers in [11].

To achieve the opyimal phase adjustment for IRS and maximize total capacity in MIMO system networks, Sirojuddin *et al.* proposed an algorithm with low complexity that is designated as dimension-wise sinusoidal maximization (DSM) [12]. In [13] and [14], by the combination of AP beamforming and IRS phase shift optimization, Lagrangian and Riemannian conjugated gradients were utilized to increase the total rate of edge users in the cell. Cui *et al.* proposed an efficient algorithm for obtaining high-quality suboptimal solutions using alternate optimization and semidefinite relaxation, which maximizes the confidentiality of legitimate communication links by collaboratively constructing the transmitted beamforming of AP and reflected beamforming of IRS [15]. A block coordinate search (BCS) algorithm was raised for multi-user maximization of the sum rate, which achieves good performance by the joint integration of IRS coordinates, phase shift matrix, THz subband allocation and power control in [16].

In light of the foregoing, the primary findings of this paper are outlined as follows.

- We investigate the system model involving intelligent reflecting surfaces (IRS) in a smart home scenario, and delve into the challenging problem of optimizing the weighted total rate. It is important to note that optimization problem of the proposed method is non-convex, posing significant difficulties in finding a solution. Therefore, we take advantage of alternating optimization algorithms to simplify the optimization process.
- In the CSI, we adopt a two-step optimization approach to address this non-convex optimizing issue. Firstly, we exploit the fractional programming approach to optimize the beamforming vector while keeping the phase shift matrix fixed. Subsequently, we utilize the Riemannian Conjugate Gradient method to get the optimal resolution for the phase-shifting matrix, when keeping fixed the beamforming vector. This iterative approach allows us to convert the initial non-convex matter into convex matter or optimize the variables sequentially.
- Simulation results show that the improved alternating optimization delivers a greater total rate compared with baseline schemes, and with a significantly lower number of iterations. Since Riemannian optimization algorithm has the characteristic of low complexity, this alternate optimization algorithm has faster convergence.

The organization of the subsequent sections of this paper is as follows. Section II illustrates the system model and formulates trouble under consideration. In Section III, an AO algorithm that integrates devise of the beamforming vector and phase shift matrix is presented to achieve weighted rate maximization. Section IV introduces the simulation results of the weighted sum rate obtained by the impoved AO method, and presents the advantages of the method. In Section V, the conclusion is provided.

II. SYSTEM MODEL AND PROBLEM FORMULATION

We investigate a downlink communication scenario in a multi-user smart home system employing IRS as depicted in Fig. 1. The system includes an AP with M antennas, IRS with N reflection elements and K single-antenna users. It is well known that these users are mainly smart devices such as smart light bulbs and smart TVs. Moreover, in contrast to the system where user receives signal from the AP, there are not only direct channels but also reflection channels that are reflected by the IRS due to the use of the IRS. And the reflected channel is constructively added to the direct channel. In [17], Huang *et al.* explored the utilization of passive intelligent mirroring to strengthen total rate of multi-user systems. However, in the system modeling of [17], the direct link between the AP and users was not considered, and only indirect channel and reflection channel were considered. We take into account a case where quasi-static fading affects all channels. We assume that the channel state informations for three channels are completely known in the explanation below.

In this paper, we denote the baseband equivalent channels from the AP to the IRS, from the IRS to user k, and from the AP to user k as $\boldsymbol{h}_r \in \mathbb{C}^{N\times M}$, $\boldsymbol{h}_{r,k} \in \mathbb{C}^{1\times N}$, and $\boldsymbol{h}_{d,k} \in \mathbb{C}^{1\times M}$, respectively. We define $\theta_n = e^{j\varphi_n}$ and introduce diagonal matrix $\boldsymbol{\Theta} = diag(\theta_1, \theta_2, \cdots, \theta_N) \in \mathbb{C}^{N\times N}$, where $\varphi_n \in [0, 2\pi)$ shows the phase shift of the n-th IRS component. Additionally, the transmitted signals by the AP are represented in the communication system: $\boldsymbol{X} = \sum_{k=1}^{K} \boldsymbol{w}_k s_k$, where $\boldsymbol{w}_k \in \mathbb{C}^{M\times 1}$ is the transmit beamforming vector for the k-th user, and s_k denotes desired signal for the k-th user with $s_k \sim \mathcal{CN}(0,1)$.

In addition, the baseband signal received by the users can be expressed as

$$\begin{aligned} y_k &= (\boldsymbol{h}_{d,k} + \boldsymbol{h}_{r,k}\boldsymbol{\Theta}\boldsymbol{h}_{\boldsymbol{r}})\,\boldsymbol{X} + n_k, \qquad k = 1,...,K \\ &= (\boldsymbol{h}_{d,k} + \boldsymbol{h}_{r,k}\boldsymbol{\Theta}\boldsymbol{h}_{\boldsymbol{r}}) \sum_{k=1}^{K} \boldsymbol{w}_k s_k + n_k \end{aligned} \tag{1}$$

where $n_k \sim \mathcal{CN}(0, \sigma_k^2)$ denotes independent identically distributed the additive white Gaussian noise (AWGN) vector at the k-th user. Accordingly, based on the information provided above, the SINR received by user k in a multi-user communication system can be expressed as

$$SINR_k = \frac{\mid (\boldsymbol{h}_{d,k} + \boldsymbol{h}_{r,k}\boldsymbol{\Theta}\boldsymbol{h_r})\, \boldsymbol{w}_k \mid^2}{\sum_{i \neq k}^{K} \mid (\boldsymbol{h}_{d,k} + \boldsymbol{h}_{r,k}\boldsymbol{\Theta}\boldsymbol{h_r})\, \boldsymbol{w}_i \mid^2 + \sigma^2}, \forall k \quad (2)$$

In this paper, we adopt a time division duplexing protocol in the IRS-assisted system for both uplink and downlink broadcasts. Considering that the IRS is a passive reflection device, we assume channel reciprocity for downlink CSI acquisition based on uplink training, as discussed in [18]. In this article, we just think about downlink channel in the system. We define $\boldsymbol{W} = [\boldsymbol{w}_1, \boldsymbol{w}_2, ..., \boldsymbol{w}_k] \in \mathbb{C}^{M \times K}$. The purpose of our research is to optimize the weighted sum rate of multi-users in the system by optimizing the beamforming vector at AP and the phase shift vector at the IRS in [19]. Thus, the above-mentioned issue is represented as

$$\text{(P1)}: \quad \max_{\boldsymbol{W},\boldsymbol{\Theta}} \quad \sum_{k=1}^{K} \omega_k log_2(1 + SINR_k) \quad (3)$$

$$\text{s.t.} \quad \sum_{k=1}^{K} \|\boldsymbol{w}_k\|^2 \leq P_T \quad (4)$$

$$\mid \theta_n \mid = 1, \quad n = 1, \cdots, N, \quad (5)$$

where ω_k denotes the priority of the multiple users. (4) is the transmit power restriction of AP, in addition P_T expresses the maximum total power consumed at the AP. We can utilize $f(\boldsymbol{W}, \boldsymbol{\Theta})$ to describe the objective function of $P1$.

$$f(\boldsymbol{W}, \boldsymbol{\Theta}) = \sum_{k=1}^{K} \omega_k log_2(1 + SINR_k) \quad (6)$$

III. IMPROVED ALTERNATING OPTIMIZATION ALGORITHM

Obviously, P1 is not an easy problem to solve. The optimization problem in (4) presents a challenging non-convex problem with interconnected optimization variables. We adopt fractional programming method to simplify optimization problem [20]. Convert the $f(\boldsymbol{W}, \boldsymbol{\Theta})$ problem into an optimization of two steps by the AO algorithm, respectively. The first step is to fix the phase shift vector $\boldsymbol{\Theta}$, and optimize $\boldsymbol{W}$. By using fractional programming, the optimal value of this problem can be obtained. The second step is the optimization of the phase shift vector $\boldsymbol{\Theta}$ with fixing beamforming vector $\boldsymbol{W}$. We can utilize the RCG algorithm to find the optimal value. Firstly, based on Lagrangian dual transformation, a new variable $\boldsymbol{\alpha}$ is introduced to transform the objective function of $f(\boldsymbol{W}, \boldsymbol{\Theta})$ into

$$\begin{aligned} f(\boldsymbol{W}, \boldsymbol{\Theta}, \boldsymbol{\alpha}) = \sum_{k=1}^{K} [&\omega_k log_2(1 + \alpha_k) - \omega_k \alpha_k \\ &+ \frac{\omega_k (1 + \alpha_k) SINR_k}{1 + SINR_k}] \end{aligned} \quad (7)$$

where $\boldsymbol{\alpha} = [\alpha_1, \alpha_2, ..., \alpha_k]^T$. If we fix $\boldsymbol{\alpha}$, the above formula can be simplified as

$$\begin{aligned} f_1 &= \sum_{k=1}^{K} \frac{g_k SINR_k}{1 + SINR_k} \\ &= \sum_{k=1}^{K} \frac{g_k \mid (\boldsymbol{h}_{d,k} + \boldsymbol{h}_{r,k}\boldsymbol{\Theta}\boldsymbol{h}_r)\boldsymbol{w}_k \mid^2}{\sum_{i=1}^{K} \mid (\boldsymbol{h}_{d,k} + \boldsymbol{h}_{r,k}\boldsymbol{\Theta}\boldsymbol{h}_r)\boldsymbol{w}_i \mid^2 + \sigma^2} \end{aligned} \quad (8)$$

where $g_k = \omega_k(1 + \alpha_k)$. If we fix $\boldsymbol{\Theta}$, α_k has closed-from solution, $\alpha_k = SINR_k$. Then, P1 can be shown as

$$\begin{aligned} (P2): \quad &\max_{\boldsymbol{W}} \quad f_1(\boldsymbol{W}) \\ &s.t. \quad \sum_{k=1}^{K} \|\boldsymbol{w}_k\|^2 \leq P_T \end{aligned} \quad (9)$$

From (8), we can see that the inverse matrix needs to be solved. So we perform a quadratic transformation of (8) to get the solution of the inverse matrix. Let $\boldsymbol{h}_k = \boldsymbol{h}_{d,k} + \boldsymbol{h}_{r,k}\boldsymbol{\Theta}\boldsymbol{h}_r$. Introducing a variable ρ_k for which a closed-form solution exists, it can be writtrn as

$$\begin{aligned} f_1(\boldsymbol{W}, \rho) = \sum_{k=1}^{K} [&2\sqrt{g}_k Re\{\rho_k^* \boldsymbol{h}_k \boldsymbol{w}_k\} \\ &- \mid \rho_k \mid^2 (\sum_{i \neq k}^{K} \mid \boldsymbol{h}_k \boldsymbol{w}_i \mid^2) + \sigma^2] \end{aligned} \quad (10)$$

Similarly, the optimization for $f_1(\boldsymbol{W})$ uses AO method. $f_1(\boldsymbol{W}, \rho)$ is a concave function for both $\boldsymbol{W}$ and ρ. $f_1(\boldsymbol{W}, \rho)$ takes partial derivatives with respect to $\boldsymbol{W}$ and ρ respectively, and sets their partial derivatives to 0, so as to find their closed form solutions. ρ_k has an optimal value that $\rho_k' = \frac{\sqrt{g}_k \boldsymbol{h}_k \boldsymbol{w}_k}{\sum_{i \neq k}^{K} |\boldsymbol{h}_k \boldsymbol{w}_i|^2 + \sigma^2}$. Therefore, the optimal beamforming vector can be got

$$\boldsymbol{w}_k' = \sqrt{g}_k \rho_k (\lambda_0 I_M + \sum \mid \rho_k \mid^2 \boldsymbol{h}_i \boldsymbol{h}_k^H)^{-1} \boldsymbol{h}_k \quad (11)$$

And the optimal precoding beamforming vector is substituted into the SINR expression to optimize the phase shift matrix. According to the previous conclusion, the P1 majorization problem can be described as

$$\begin{aligned} (P3): \quad &\max_{\boldsymbol{\Theta}} \quad f_1(\boldsymbol{\Theta}) = \sum_{i=1}^{K} \frac{g_k \mid \boldsymbol{h}_k \boldsymbol{w}_k' \mid^2}{\sum_{i \neq k}^{K} \mid \boldsymbol{h}_k \boldsymbol{w}_i' \mid^2 + \sigma^2} \\ &s.t. \quad \mid \theta_n \mid = 1, \quad n = 1, \cdots, N, \end{aligned} \quad (12)$$

Let $\boldsymbol{a}_{k,i} = \boldsymbol{h}_{d,k} \boldsymbol{w}_i'$ and $\boldsymbol{b}_{k,i} = diag(\boldsymbol{h}_{r,k} \boldsymbol{G} \boldsymbol{w}_i')$. Therefore, the optimization objective function of the P3 problem is simplified to

$$f_1(\boldsymbol{\theta}) = \sum_{i=1}^{K} \frac{g_k \mid \boldsymbol{a}_{k,k} + \theta^H \boldsymbol{b}_{k,k} \mid^2}{\sum_{i \neq k}^{K} \mid \boldsymbol{a}_{k,i} + \theta^H \boldsymbol{b}_{k,i} \mid^2 + \sigma^2} \quad (13)$$

Similarly, we can also use the fractional programming method (Lagrangian dual transformation and quadratic transformation) to simplify the formula (13) and make it easy to calculate. By a variety of optimizations, simplification of the formula can be obtained

$$f_2(\boldsymbol{\theta}) = -\boldsymbol{\theta}^H \mathcal{A} \boldsymbol{\theta} + 2\mathrm{Re}\{\boldsymbol{\theta}^H \mathcal{B}\} + \mathcal{C} \tag{14}$$

where

$\mathcal{A} = \sum_{k=1}^{K} \mid \varepsilon_k \mid^2 \sum_{i=1}^{K} \boldsymbol{a}_{k,i} \boldsymbol{b}_{k,i}^H$,

$\mathcal{B} = \sum_{k=1}^{K} (\sqrt{g}_k \varepsilon_k^* \boldsymbol{a}_{k,k} - \mid \varepsilon_k \mid^2 \sum_{i=1}^{K} \boldsymbol{a}_{k,i}^* \boldsymbol{b}_{k,i})$,

$\mathcal{C} = \sum_{k=1}^{K} (2\sqrt{g}_k Re\{\varepsilon_k^* \boldsymbol{a}_{k,k}\} - \mid \varepsilon_k \mid^2 (\sigma^2 + \sum_{i=1}^{K} \mid \boldsymbol{a}_{k,i} \mid^2))$

and ε is a closed form solution. In Euclidean space, this issue may not be easy to solve. So it can be transformed into Riemannian manifolds to consider the problem. Hence, we can apply the RCG algorithm [21] to find the optimal solution of $\boldsymbol{\theta}$, and (14) can be expressed as

$$\min_{\boldsymbol{\theta}} \quad f_2(\boldsymbol{\theta}) = \boldsymbol{\theta}^H \mathcal{A} \boldsymbol{\theta} - 2\mathrm{Re}\{\boldsymbol{\theta}^H \mathcal{B}\} \tag{15}$$

Thus, we describe the Riemannian conjugated gradient solution procedure.

1) The search direction: The direction of a Riemannian manifold is the direction on the sphere. Therefore, the gradient direction of the n-th iteration of Riemannian optimization is

$$\eta_n = -\mathrm{grad} f_2(\boldsymbol{\theta}_n) + \xi \Gamma_{\eta^n} \tag{16}$$

where

$$\mathrm{grad} f_2(\boldsymbol{\theta}_n) = \mathcal{A}\boldsymbol{\theta}_n + \mathcal{A}\boldsymbol{\theta}_n^* - 2\mathrm{Re}\{\mathcal{B}\}, \tag{17}$$

ξ denotes the Riemannian conjugated gradient update parameter, and $\Gamma_{\eta^n} = \eta^{n-1} - \mathrm{Re}\{\eta^n \odot \boldsymbol{\theta}^*\} \odot \boldsymbol{\theta}$ is the vector transport function.

2) Retraction operation: In order to guarantee that the iteration point remains on the manifold, the contraction operator is utilized to define the "addition" operation on the manifold

$$R_{\boldsymbol{\theta}^n} = \frac{(\boldsymbol{\theta} + \alpha \eta^{n-1})_n}{\parallel (\boldsymbol{\theta} + \alpha \boldsymbol{\eta}^{n-1})_n \parallel} \tag{18}$$

where α_n is the Armijo step size.

3) Updated descent: The update in the tangent space is

$$\boldsymbol{\theta}^{n+1} = R_{\boldsymbol{\theta}^n}(-\alpha_n \eta^n) \tag{19}$$

Based on the above process, we can easily get the optimum solution of $\boldsymbol{\theta}$ by [21].

The pseudo code for addressing problem (P1) is wrapped up in Algorithm 1.

TABLE I. Comparision between traditional algorithm and the proposed algorithm

Algorithm / Method	Traditional Algorithm [20]	The Proposed Algorithm
Beamforming Design	fractional programming	fractional programming
Phase Optimization	successive convex approximation	Riemannian conjugated gradient

Fractional programming can transform fractional problems into linear programming problems and reduce the difficulty of solving the problems. Riemannian conjugated gradient algorithm greatly can bring down the computational complexity. Since the phase optimization constraint is a complex circle, it can be difficult to compute in Euclidean space, so the variable optimization in popular space is considered. From TABLE I, we can observe that this paper has made some improvements on [20].

Algorithm 1 AO algorithm for solving problem (P1)

Initialize $\boldsymbol{W}_0, \boldsymbol{\Theta}_0$ to feasible values.
Get the equivalent channel $\boldsymbol{h}_k$.
repeat
  Update the SINR $SINR_k$ based on (2) and then we can get optimal $\boldsymbol{\alpha}_i$ that $\boldsymbol{\alpha}_i = SINR_k$;
  Obtain closed-form solution of ρ_k, and update transmit beamforming vector $\boldsymbol{W}_i$ based on $\boldsymbol{w}_k' = \sqrt{g}_k \rho_k (\lambda_0 I_M + \sum \mid \rho_k \mid^2 \boldsymbol{h}_i \boldsymbol{h}_k^H)^{-1} \boldsymbol{h}_k$;
  Update phase shift vector $\boldsymbol{\Theta}_i$ by Riemannian conjugated gradient algorithm;
until The value of function $\frac{\omega_k(1+\alpha_k)SINR_k}{1+SINR_k}$ based on (7) converges.

Output: weighted sum rate of multiple users based on $\sum_{k=1}^{K} \omega_k log_2(1 + SINR_k)$ geted by optimal beamforming vector W_i and optimal phase shift $\boldsymbol{\Theta}$.

TABLE II. Simulation setting

Parameter	Information
AP number	M = 4
AP location	(0 m,0 m)
users number	K = 4
users location	(10 m,4 m) with radius 5 m
IRS location	(7 m,6 m)
Rician factor	$\varepsilon_0 = 10$

IV. Simulation Results

Finally, this AO algorithm is verified by virtual indoor simulation test. In this part, numerical simulations are presented for analyzing the results of a multi-user communication system. We take into account the IRS-based smart home application scenario illustrated in Fig. 2. The system parameters can be seen in TABLE II. This model is established on the foundation of antenna array theory, specifically tailored for massive MIMO channel modeling, as discussed in [18]. In the context of smart home scenarios, where communication typically occurs indoors, the channels between the AP and users may experience signal attenuation due to the presence of walls. In this paper, we assume that the direct link channel $\boldsymbol{h}_{d,k}$ exhibits Rayleigh fading, while indirect link channels $\boldsymbol{h}_r$ and reflect link channel $\boldsymbol{h}_{r,k}$ are assumed to follow Rician fading, as described in reference [22]. The Rician channels can be expressed as

$$\boldsymbol{h}_r = \sqrt{\frac{\varepsilon_0}{\varepsilon_0 + 1}} \boldsymbol{h}_{r_{LoS}} + \sqrt{\frac{1}{\varepsilon_0 + 1}} \boldsymbol{h}_{r_{NLoS}} \tag{20}$$

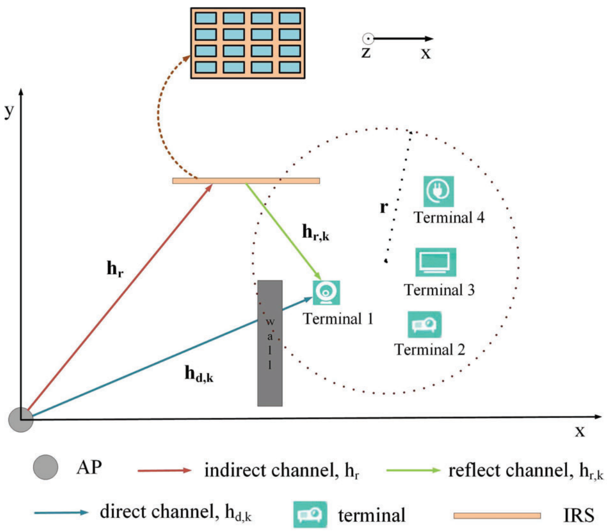

Fig. 2. Smart home deployment scenario.

$$
\boldsymbol{h}_{r,k} = \sqrt{\frac{\varepsilon_0}{\varepsilon_0+1}}\boldsymbol{h}_{r,k_{LoS}} + \sqrt{\frac{1}{\varepsilon_0+1}}\boldsymbol{h}_{r,k_{NLoS}} \tag{21}
$$

where h_{LoS} expresses the line of sight component, h_{NLoS} represents the non-line of sight component modeled by Rayleigh fading. Besides, the path-loss L is represented by the 3GPP propagation environment [23]. In addition, ω_k in (3) is determined by the path ratio of different users, and $\sum_{k=1}^{K}\omega_k = 1$.

To show the proposed AO algorithm's innovation, we compared our algorithm with the following schemes.

1) ***Without IRS***: There is only a direct channel between the AP and users, and without IRS'elements means that no IRS auxiliary reflection channel.
2) ***IRS with random phase***: Beamforming vector $\boldsymbol{W}$ is obtained by weighted minimum mean-square error. And the phase shift vector θ is randomly generated, which means the beam is randomly reflected.
3) ***Karush-Kuhn-Tucker conditions***: The KKT conditions are indispensable criteria for a result to be deemed optimal in this paper, preserving the original meaning. Hence, in the case of initialization, the maximum output can be optimized if it is run enough times.

The relationship between the weighted sum rate (WSR) and the number of IRS elements is depicted in Fig. 3. We choose a fixed transmit power level of $P_t = 10$ dBm. It is evident that increase the sum rate. In the absence of IRS, there is no significant change, and the gain from random phase is relatively small. Although the gain of the algorithm based on the KKT condition is not small, the AO-based algorithm outperforms the three benchmark algorithms. Obviously, by adjusting the number of IRS elements, it can be feasible to somewhat enhance the channels' rate performance.

Figure 4 is the variation of WSR with the transmission power at the network card. As the transmit power increases, the growth rate of the proposed algorithm is better than other schemes. And at the same rate, the transmission power required by the AO algorithm is smaller than that of the other three algorithms, which reduces the power resources to a certain extent. At this point, we set the number of elements $N = 200$. As evident from Fig. 4, when $P_t = 10$ dBm, the sum rate is basically the same as shown in Fig. 3. The feasibility of the algorithm is verified.

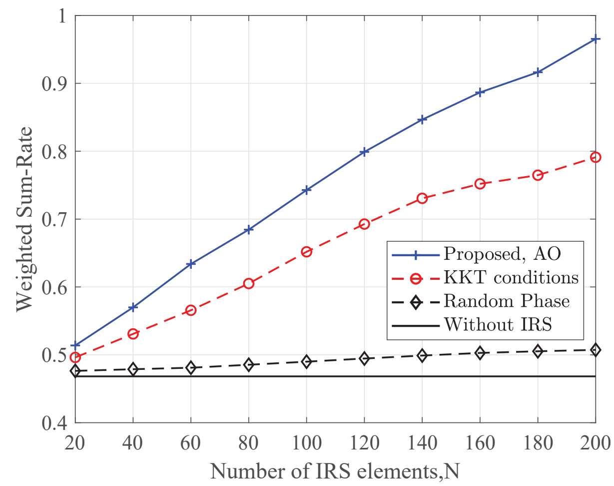

Fig. 3. Weighted Sum-Rate vs number of IRS elements.

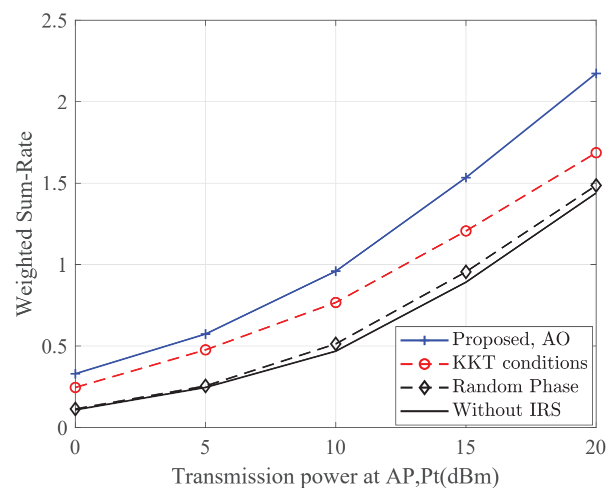

Fig. 4. Weighted Sum-Rate vs transmission power at AP.

In Fig. 5, we define the transmit power of the AP to be 10 dBm and consider 200 elements of the IRS to investigate convergence characteristics of the optimization algorithm. Fig. 5 shows that the alternating optimization technique iterates more quickly than other algorithms do. Specifically, the method that uses the AO algorithm of fractional programming and Riemannian gradient descent can modify the complexity of computation and decrease the amount of computation, thus obtaining the more rapid convergence. Therefore, we can

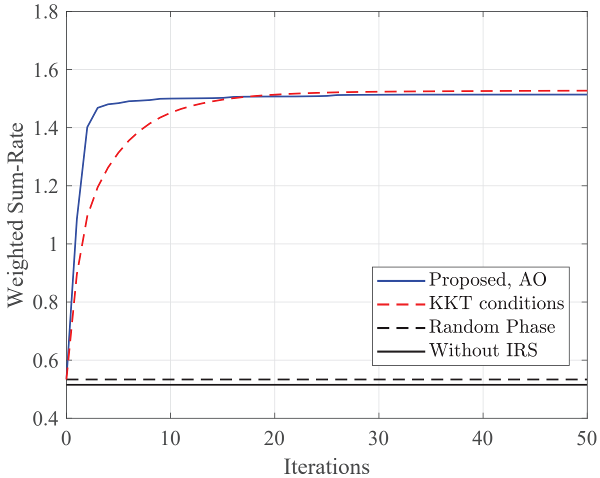

Fig. 5. Weighted Sum-Rate vs number of iterations.

obtain excellent results in regards to the sum rate with a small number of iterations.

V. Conclusion

We researched multiple devices with IRS-based smart home system model in this paper. In a perfect CSI setting, the weighted sum rate of numerous users was increased by an AO algorithm that optimizes beamforming with fractional programming and phase shift matrix with Riemannian conjugated gradient algorithm. The simulation results shown that under the same transmission power constraints, using IRS signal transmission yields better performance, and the algorithm is outperformed benchmark algorithms. As the number of IRS components has increased, the weighted sum rate can be further enhanced. Under the same rate requirement, optimization algorithm can also require less transmission power at the AP, thus reducing the resource overhead. In addition, it is indicated that the algorithm is feasible and decrease the computational complexity well. To some extent, the algorithm also reduces the communication cost.

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