Multi-Objective Evolutionary Algorithm Aided Multi-User Communication

Yijie Tong, Xinyu Chen, and Jialin Li

***Abstract*—Reconfigurable intelligent surfaces (RISs) have drawn considerable attention from the research community recently. RISs create favorable propagation conditions by controlling the phase shifts of reflected waves at the surface, thereby enhancing wireless transmissions. In this paper, we study a downlink multi-user system where the transmission from a multi-antenna base station (BS) to various users is achieved by an RIS reflecting the incident signals of the BS towards the users. A normal RIS configuration optimization gives a sum rate maximization (SRM)-based design to maximize the sum rate of all users in the cell, however, without taking the individual users rates into account, which significantly degrades the rates of the users with weaker channel conditions. Such method will possibly give a low quality service to the weakest user. Hence, the base station (BS) should have the flexibility to intelligently decide whether it needs to maximize the sum rate or the fairness among users, or to strike a good balance between them. Both performance metrics, the sum rate and the fairness among users are crucial performance metrics that have to be considered in 5G and beyond wireless networks. A hybrid beamforming scheme is proposed and the sum-rate mixed fairness optimization problem is formulated.**

Specifically, continuous digital beamforming and discrete RIS-based analog beamforming are performed at the BS and the RIS, respectively, and a multi-objective evolutionary algorithm is designed to solve this problem. And the following experiments prove the correctness of our algorithm which can reach a high sum rate balanced with reasonable fairness.

***Index Terms*—Reconfigurable intelligent surface, hybrid beam-forming, multi-user communications, limited discrete phase shifts, multi-objective evolutionary algorithm**

I. Introduction

THE past decade has witnessed an enormous increase in the number of mobile devices [1], triggering urgent needs for high-speed and seamless data services in future wireless systems. To meet such demands, one fundamental issue is how to improve the link quality in the complicated time-varying wireless environments involving unpredictable fading and strong shadowing effects. Various technologies have been developed such as relaying [2] and massive multiple input and multiple output (MIMO) systems [3], aiming to actively strengthen the target signals by forwarding and taking advantage of multi-path effects, respectively. However, these techniques require extra hardware implementation with inevitable power consumption and high complexity for signal processing, and the quality of service is also not always guaranteed in harsh propagation environments.

A more recently proposed technology involves reconfigurable intelligent surfaces (RISs), which are an ultra thin surfaces inlaid with multiple sub-wavelength scatters, i.e., RIS elements, whose electromagnetic response (such as phase shifts) can be controlled by simple programmable PIN diodes [6]. Based on the ON/OFF functions of PIN diodes, only a limited number of discrete phases shifts can be achieved by an RIS [7]. Instead of scattered waves emanated from traditional antennas, the sub-wavelength separation between adjacent RIS elements enables the refracted and reflected waves to be generated via superposition of incident waves at the surface [8]. Benefitting from such a programmable characteristic of molding the wavefronts into desired shapes, the RIS serves as a part of reconfigurable propagation environment such that the received signals are directly reflected towards the receivers without any extra cost of power sources or hardware [9], thereby improving the link quality and coverage.

To exploit the potential of RIS techniques, many existing works have considered the RIS as a reflection-type surface deployed between sources and destinations in either point-to-point communications [5], [10]– [12] or multi-user (MU) systems [13]– [17]. In [11], a point-to-point RIS-assisted multi-input single-out system has been investigated where the beamformer at the transmitter and continuous phase shifts of the RIS are jointly optimized to maximize the sum rate. In [15], a channel estimation protocol has been proposed for a multi-user RIS-assisted system and the continuous phase shifts have been designed to maximize the minimum user date. In [16], the authors have minimized the transmit power of the access point by optimizing the continuous digital beamforming and discrete phase shifts. An algorithm has been designed for the single-user case and extended to the multiuser case. In [17], the authors have considered a downlink RIS based multi-user MISO network and studied the joint active and passive beamforming problem to maximize the weighted sum rate. An iterative algorithm has been designed for the continuous phase shift case, which can also be extended to the discrete case.

We aim to design an hybrid beamforming (HBF) scheme for the RIS-based multi-user system with limited discrete phase shifts to maximize the sum rate.

Fairness is also an important issue in the communication area. Multiple access technique, along with other disruptive technologies, such as massive multiple-input multiple-output (MIMO) and mm Wave communication, has the potential to further improve the performance of the fifth generation (5G) and beyond wireless networks [18], [19]. Recently, different rate-aware beamforming designs have been proposed for multiple-input single-output (MISO) NOMA systems. For example, the sum rate maximization (SRM)-based design maximizes the sum rate of all users in the cell, however, without taking the individual users rates into account [20]. This approach significantly degrades the rates of the users with weaker channel conditions. To overcome this issue, a rate-fairness-based design has been developed through the weighted sum-rate maximization (WSRM). In WSRM, higher weights are assigned to weaker users' rates to maintain the fairness between users in terms of their achievable rates. However, none of these conventional rate-aware-based designs consider either the instantaneous rate-requirements of the users, or the variations of the users' channel strengths due to the mobility of the users. For example, SRM-based design is an appropriate beamforming design when the users have similar channel strengths. However, the SRM-based design is not capable of achieving a reasonable throughput for all users in a system where the channel strengths of the users vary significantly. Such cases, the weakest user will suffer from low quality of service. In particular, both performance metrics, the sum rate and the fairness among users are crucial performance metrics that have to be considered in 5G and beyond wireless networks [21]. Hence, the base station (BS) should have the flexibility to intelligently decide whether it needs to maximize the sum rate or the fairness among users, or to strike a good balance between them. The fairness index (FI) has been used to measure the fairness between users in terms of their achievable rates [22]. In particular, the FI of the system with K users is defined as follows [23], [24]:

$$\boldsymbol{FI} = \frac{(\sum_{i=1}^{K} \boldsymbol{R}_i)^2}{K \sum_{i=1}^{K} \boldsymbol{R}_i^2} \tag{1}$$

where R_i denotes the achieved rate of the i^{th} user (u_i). The best fairness can be achieved when FI is one. Note that the FI and sum rate are conflicting performance metrics, which means that maximizing the sum rate will degrade the FI, and vice versa, especially with users with significantly different channel strengths.

A multi-objective evolutionary algorithm is designed to exploit the balance between sum rate and fairness. Our main contributions can be summarized as follows.

- *Fairness issue has never been considered in RIS communication system before and we give a first try.*
- *The problem is formulated as a two object optimization problem, which is unnecessary for a balance parameter to give a overall optimization.*
- *Since the sum rate and fairness value have conflicts with each other, we use the multi-objective evolutionary algorithm to formulate this pair of value as good as possible. Then a set of this pair of value can help the user to do the decision. Our method has many advantages. Multi objective evolutionary algorithm can do multiple variables evaluation at the same time, and there is no need to decouple variables like the semi-define method, which gives a high accuracy to the result.*
- *Experiments empirically prove the correctness of our method.*

The rest of this paper is organized as follows. In Section II, we introduce the system model of the downlink RIS-based MU multi-antenna system. In Section III, a multi-object genetic algorithm is designed to balance fairness and sum rate. In Section IV, We give some experiments to test the result of our algorithm.

II. System Model

The system is the same with that in Hybrid Beamforming for Reconfigurable Intelligent Surface based Multi-User Communications: Achievable Rates With Limited Discrete Phase Shifts [28].

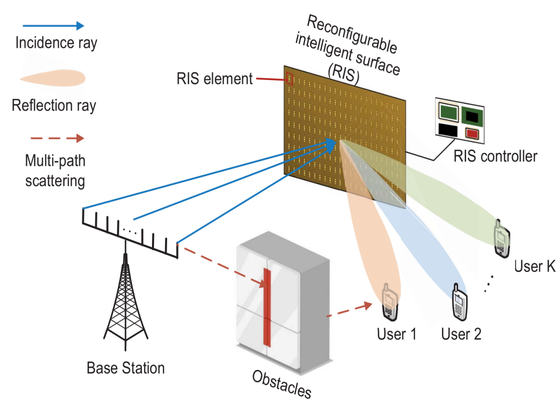

Fig. 1. System model of the RIS-based downlink multi-user communication system.

A. Scenario Description

Consider a downlink multi-user communication system as shown in Fig. 1 where a BS (base station) equipped with N_t antennas transmits to K single-antenna users. It is very common in the real world that the BS - user link is not stable due to the complicated and dynamic wireless environment involving unexpected fading and potential obstacles. Compared with setting more base station, to deploy an economic and flexible RIS is more attractive. We set the RIS between the BS and users, which reflects the signals from the BS and directly projects to the users by actively shaping the propagation environment into a desirable form.

An RIS consists of $N_R \times N_R$ electrically controlled RIS elements as shown in Fig. 1, each of which is a sub-wavelength meta-material particle with very small features. An RIS controller can control the ON/OFF state of a RIS element, thereby manipulating the electromagnetic response of the RIS elements towards incident waves. So the whole configuration of one RIS can be regarded as a matrix composed of ON/OFF state of RIS elements. Due to the nature of RIS element, the RIS requires no extra active power sources nor do not have any signal processing capability such as decoding like a exchange station. In other words, it serves as a low-cost reconfigurable phased array that only relies on the combination of multiple programmable radiating elements to realize a desired transformation on the transmitted, received, or reflected waves.

B. Reconfigurable Intelligent Surface With Limited Discrete Phase Shifts

The RIS is achieved by the b-bit re-programmable meta-material, as shown in Fig. 2,which has been implemented as a set of radiative elements layered on a guiding structure following the wave guide techniques, forming a 2-dimensional (2D) planar antenna array [25]. Each RIS element is encoded by b PIN diodes to conduct 2^b possible phase shifts to reflect the radio wave. These elements only vibrate in resonance with the incoming waves over a narrow band centering at the resonance frequency, due to the frequency selective nature of the meta-materials. Without loss of generality, we denote the frequency response of each element (l_1, l_2) at the l_1-th row and l_2-th column of the 2D RIS within the considered frequency range as q_{l_1,l_2}, 0≤l_1, l_2≤NR-1.Since the RIS is b-bit controllable, 2^b possible configuration modes (i.e., phases) of each q_{l_1,l_2} can be defined according to the Lorentzian resonance response [1].

$$q_{l_1,l_2} = \frac{j + e^{j\theta_{l_1,l_2}}}{2}, \theta_{l_1,l_2} = \frac{m_{l_1,l_2}\pi}{2^{b-1}}, \tag{2}$$

$$m_{l_1,l_2} \epsilon \{0, 1, ..., 2^b - 1\}, 0 \leq l_1, l_2 \leq N_R - 1, \tag{3}$$

where θ_{l_1,l_2} denotes the phase shift of RIS element (l_1, l_2). For convenience, we refer to b as the number of quantization bits.

C. Reflection-Dominated Channel Model

In this subsection, we model the channel $h^{k,n}_{l_1,l_2}$ between antenna 0 ≤ n ≤ N_t - 1 of the BS and user k passing the RIS element (l_1,l_2). Let $D^{(n)}_{l_1,l_2}$ and $d^{(k)}_{l_1,l_2}$ denote the distance between antenna n and RIS element (l_1, l_2), and that between user k and RIS element (l_1, l_2), respectively. The channel h(between each BS antenna 1 ≤ n ≤ N_t and user k via RIS element (l_1, l_2) is given by [27]

$$h^{(k,n)}_{l_1,l_2} = (D^{(n)}_{l_1,l_2} \cdot d^{(k)}_{l_1,l_2})^{-\alpha} \cdot e^{-j\frac{2\pi}{\lambda}(D^{(n)}_{l_1,l_2} + d^{(k)}_{l_1,l_2})}, \tag{4}$$

where α is the path loss parameter.

D. Hybrid Beamforming Scheme

1) Digital Beamforming at the BS: The BS first encodes K different data steams via a digital beamformer, $\boldsymbol{V}_D$, of size N_t × K, satisfying N_t ≥K.

2) Transmission model: The transmission matrix $\boldsymbol{F}$ is of size K × N_t , in which each element $f_{k,n}$ is defined as

$$f_{k,n} = Tr(\phi^{(k)} \boldsymbol{Q}^T \boldsymbol{H}^{(k,n)}), \tag{5}$$

where $\boldsymbol{Q}$ is a $N_R \times N_R$ matrix consisting of the phase shifts q_{l_1,l_2} , and $\boldsymbol{H}^{(k,n)}$ is the $N_R \times N_R$ channel matrix between each BS antenna n and user k, consisting of elements $h^{k,n}_{l_1,l_2}$.

E. Sum Rate Maximization Problem

The achievable rate of user k can be given by

$$R_k = log_2(1 + \frac{|\boldsymbol{F}_k^H \boldsymbol{V}_{D,k}|^2}{\sum\limits_{k' \neq k} |\boldsymbol{F}_k^H \boldsymbol{V}_{D,k'}|^2 + \sigma^2}), \tag{6}$$

where F_k and $V_{D,k}$ denote the k-th columns of matrices F and $\boldsymbol{V}_D$ respectively and σ donates the noise. We aim to maximize the achievable rates of all users by optimizing the digital beamformer $\boldsymbol{V}_D$ and the RIS configuration q_{l_1,l_2} , as formulated below:

$$\underset{\boldsymbol{V}_D, \{q_{l_1,l2}\}}{maximize} \sum_{1 \leqslant k \leqslant K} R_k, max\boldsymbol{FI} \tag{7a}$$

subject to

$$\boldsymbol{Tr}(\boldsymbol{V}_D^H \boldsymbol{V}_D) \leqslant P_T, \tag{7b}$$

$$q_{l_1,l_2} = \frac{j + e^{j\theta_{l_1,l_2}}}{2}, 0 \leqslant l_1, l_2 \leqslant N_R - 1, \tag{7c}$$

$$\theta_{l_1,l_2} = \frac{m_{l_1,l_2}\pi}{2^{b-1}}, m_{l_1,l_2} \epsilon \{0, 1, ..., 2^b - 1\}, \tag{7d}$$

where PT is the total transmit power of the BS.

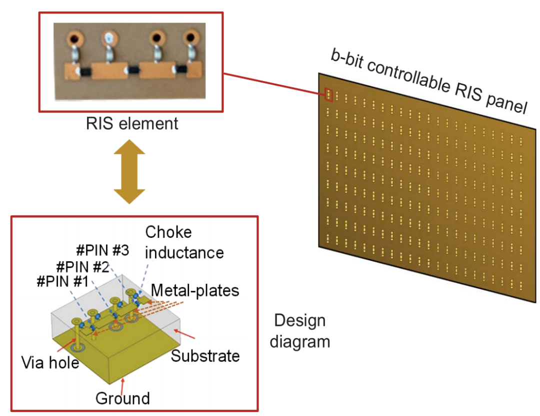

Fig. 2. Schematic structure of b-bit encoded RIS.

III. Algorithm

Note that problem we raised is a mixed integer non-convex optimization problem having variables with diverse data type as integer and complex-valued matrix. It is an enormous challenge to implement the optimization due to the coupling property. We see some workers approximately relax it to an SDP problem, which would cause inaccuracy in natural solution. Since it is an NP-hard problem dealing with coupling variables, decomposition of the problem would lead to deviations and unreliability [28]. In addition, the multi-objective problem is a new purpose. We consider both the achievable rates of all users and promote the fairness among users at same time, which means we need to control the balance and find appropriate solutions. Optimization becomes more complex due to multiple targets.

Putting the challenge into consideration, we develop a multi-objective evolutionary algorithm to solve the problem more preferably. Using evolutionary algorithm, we could make multiple variables do evaluation at the same time, which guarantees that there is no need to do decoupling and approximation and affords a better way to solve NP-hard problem.

For a better understanding the proposed method is presented in Algorithm 1 and its steps are detailed next.

1) Get the initial groups with N individuals. Randomly generate phase shifts to initial the m, then calculate the first state of digital beamforming $\boldsymbol{V}_D$.
2) Use Simulated Binary Crossover and Polynomial Mutation to do crossover and mutation for m and $\boldsymbol{V}_D$ separately.
3) Use NSGA-II (Non-dominated Sorting Genetic Algorithm) to select elite solutions.
4) Check if the stop criterion is met. If so, then return the fittest particle ($\boldsymbol{V}_D$, m). Otherwise, go to Step 2.

A. Initialization

Our final aim is to maximize the achievable rates of all users and promote the fairness among users at same time. The way is doing optimization on the digital beamformer $\boldsymbol{V}_D$ (expressed as a complex number having ρ and θ as the length and the angle of the beam separately) and the RIS configuration q_{l_1,l_2} decided by m as described in (6a) to (6d). Then we initial the group ancestor by giving first state of the variables $\boldsymbol{V}_D$ and m.

Using N to represent popsize, we get initialized group with N individuals, as the parents to do crossover and mutation to obtain new gruops.

B. Crossover and Mutation for m

1) Simulated Binary Crossover (SBX): We choose SBX as the operator of crossover, whose search power is similar to that of the single-point crossover used in binary-coded GAs, and the real-coded GAs with the SBX operator are able to perform as good or better than binary-coded GAs with the single-point crossover. Besides, SBX is found to be particularly useful in problems having multiple optimal solutions with a narrow global basin and in problems where the lower and upper bounds of the global optimum are not known a priori [30], which is suitable for the problem we developed to solve with uncertain optimal solutions.

2) Polynomial Mutation (PLM): For Multiobjective Evolutionary Algorithms (MOEAs) solving multi-objective optimization problems (MOPs), Deb and Goyal [31] proposed a variation mechanism called polynomial mutation (PLM) and this operator was improved in [32]. Since PLM allows big jumps in the search space of decision variable, the optimization process has better chances of escaping from local optima and can modify a solution when on the boundary. Moreover, PLM is used to deal with multi-objective optimization problems which fits our final goals.

C. Non-dominated Sorting Genetic Algorithm II

NSGA-II [35] has since been widely used in many applications of solving multi-objective optimization problems. Totally we produce $2N$ groups, half from parent groups and half from children groups. Half of them all would be selected as offspring. The elite solutions are selected from dominance relationship and crowding distance.

Judgment of iteration termination:

1) When the count of the iteration times is higher than x (a constant value set depending on the behavior of former practice).

2) When the difference between two contiguous versions is so small which falls in a given range.

Algorithm 1 Genetic Algorithm

Initial the group ancestors by giving first state of the variables $\boldsymbol{V}_D$ and m.
repeat
   1) Crossover and mutation for m, $\boldsymbol{V}_D$
   2) Selection same as selection operation of NSGA-II due to fast nondominate and crowding distance;
until *iteration times over or small versions difference*;
return $\boldsymbol{V}_D$, m

IV. Simulated Results

In this section, we will first introduce the result of optimizing the sum rate then introduce the result of optimizing multiple objectives the sum rate and the fair index because the multi-objectives optimization problem is based on the single optimization problem.

A. Optimization the Sum Rate

In this section, we evaluate the performance of our proposed algorithm for RIS-based HBF in terms of the sum rate. We show how the system performance is influenced by iterations of genetic algorithm, the SNR, number of users, the number of the RIS elements, and the number of quantization bits for discrete phase shifts. For comparison, the following algorithms are performed as well.

- *Random BS HBF and RIS phases*: We use the random algorithm to solve the BS HBF and the RIS phases.
- *Accurate BS HBF and random RIS phases*: We use the zero-forcing method to solve the BS HBF and the random method to solve the RIS phases.

In our simulation, we set the distance between the BS and the RIS, $D_{0,0}^{(0)}$, as 2m, and users are randomly deployed within a half circle of radius 1m centering at the RIS. The antenna array at the BS and the RIS are placed at angles of 15° and 30° to the x axis, respectively. The transmit power of the BS P_T is 20 W, the carrier frequency is 5.9 GHz, the antenna separation at the BS dB is 1 m, the RIS element separation d_R is 0.03 m. For convenience, the path loss factors of both LoS and NLoS links are the same, i.e., α = 2. We set the size of the RIS N_R^2 ranging between $3^2 \sim 10^2$. The number of antennas at the BS N_t and the number of users K are 3, the discreteness level of RIS b between 1 $\sim$ 5, and the SNR (defined as P_T $/\sigma^2$) between 0 dB $\sim$ 15 dB.

To make sure the accuracy of each result, we repeatedly simulated each result for 30 times to get the average value as the final result.

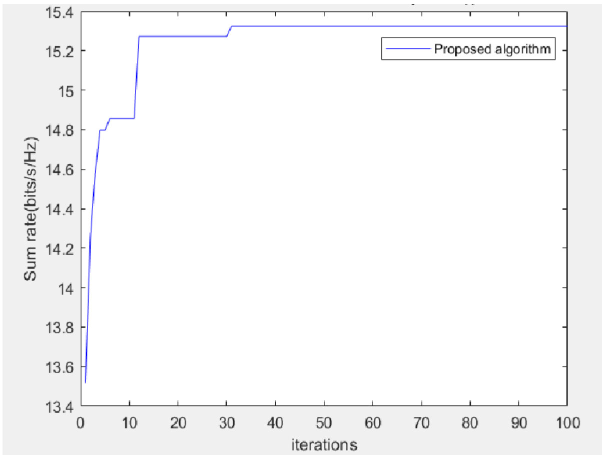

Fig. 3. Sum rate v.s. number of quantization bits b (SNR = 10dB,K = N_t = 3, N_R = 3, b = 2)

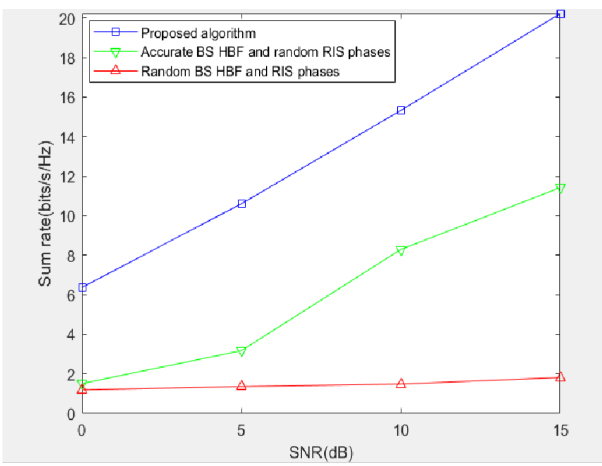

Fig. 4. Sum rate v.s. SNR (K = N_t = 3, b = 2, N_R = 3).

Fig.3 shows the number of iterations of our proposed algorithm for 3x3 RIS sizes with SNR = 10 dB, N_t = K = 3, and b = 2. We observe that the convergence speed is fast. The algorithm can converge within 50 iterations for most cases.

Fig.4 shows the sum rate of all users versus SNR, obtained by different algorithms with an RIS of size 3×3 (i.e., N_R = 3), b = 2 quantization bits for phase shifts, equal number of transmit antennas at the BS and the downlink users. The sum rate increases with SNR since more power resources are allocated by the BS. The line of our proposed algorithm is similar to the line of accurate BS HBF and random RIS phases in Fig.4. But the performance of our proposed algorithm is better than other two algorithms.

Fig.5 shows the sum rate of all users versus the size of the RIS with b = 2, N_t = K = 3. We observe that for

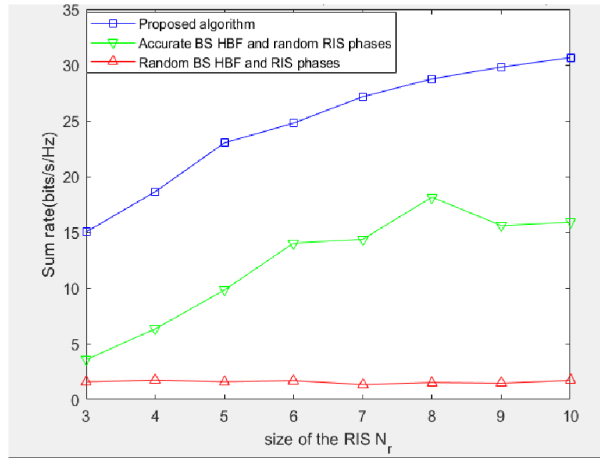

Fig. 5. Sum rate v.s. size of RIS N_R (SNR = 10dB, K = N_t = 3, b = 2).

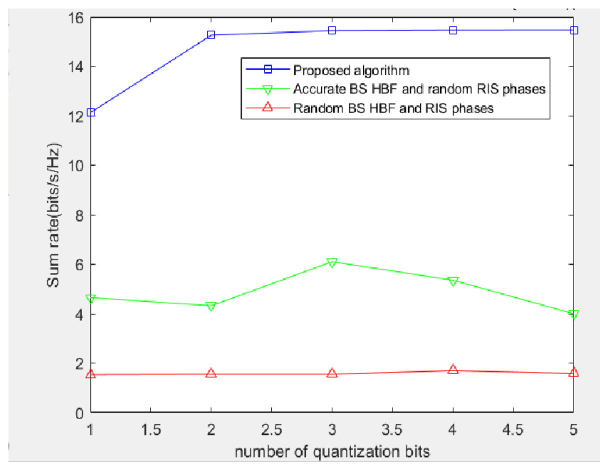

Fig. 6. Sum rate v.s. number of quantization bits b (SNR = 10dB, K = N_t = 3, N_R = 3).

our proposed algorithm, the sum rate grows rapidly with a small size of RIS and gradually flattens as the size of RIS continues to increase, and the algorithm of accurate BS HBF and random RIS phases is similar to this case. But also, the performance of our proposed algorithm is better than other two algorithms.

Fig.6 depicts the sum rate of all users versus the number of quantization bits b for discrete phase shifts in RIS configuration with SNR = 10 dB, N_t = K = 3, and N_R = 3. We observe that the performance of our proposed algorithm is better than other two algorithms and the RIS element bits nearly have no influence on the sum rate. Therefore, we remark that a small number of the phase shift bits (e.g., 2 $\tilde{3}$ quantification bits) is already enough to obtain a satisfying performance.

Above all, these simulated results indicate the efficiency of our proposed algorithms to solve the RIS-based HBF problem.

B. Optimization of the Sum Rate and the Fair Index

In this section, we evaluate the performance of our proposed algorithm for RIS-based HBF in terms of the sum rate and the fair index. We show the results of our proposed algorithm as shown in Fig.7. For comparison, the following algorithm is performed as well.

- *Random Algorithm*: We use the random algorithm to generate the BS HBF and the RIS phases.

In our simulation, we set the same configuration with Section IV.A but the number of BS antennas and the number of users are 5 to make fair index more meaningful. To make sure the accuracy of each result, we repeatedly simulated the result for 30 times to get the typical result as the final result.

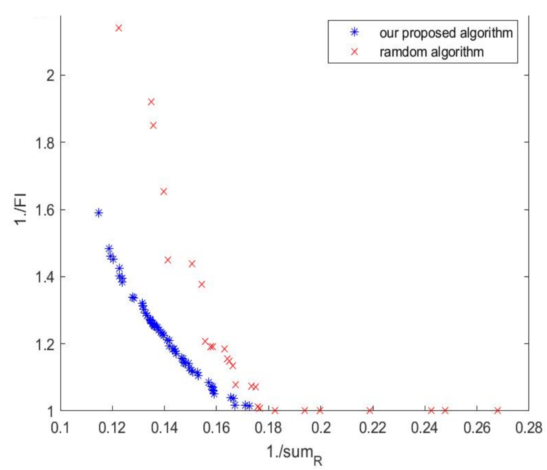

Fig. 7. Sum rate and Fair index (SNR = 5dB, K = N_t = 5, b = 2, N_R = 3).

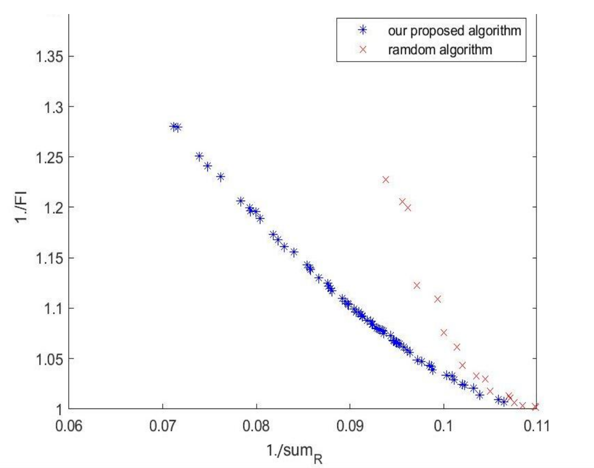

Fig. 8. Sum rate and Fair index (SNR = 10dB, K = N_t = 5, b = 2, N_R = 3).

Fig.7 shows the final result of sum rate and fair index with the SNR is 5dB, the RIS size is 3×3 (i.e., N_R = 3), b = 2 quantization bits for phase shits, and the N_t = K = 5. The X-axis represents one divides by the sum rate, the Y-axis represents one divides by the fair index FI. The closer the point to the coordinate origin, the better this point is because the small X value means large sum rate and the small Y value means high fair index. Fig.7 shows the result of our proposed algorithm is closer to the coordinate origin compared with the result of the random algorithm . And the result of our proposed algorithm forms a smooth curve which is convenient to choose the fair index and sum rate needed.

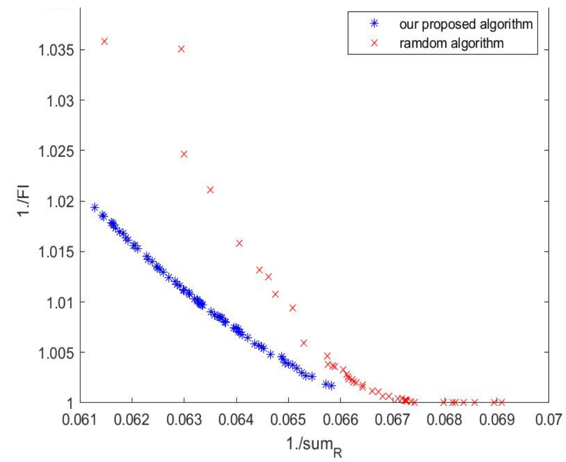

Fig. 9. Sum rate and Fair index (SNR = 15dB, K = N_t = 5, b = 2, N_R = 3).

Fig.8 is the result with SNR is 10dB and Fig.9 is the result with SNR is 15dB. Compared with the three pictures, we found that the larger the SNR is, the larger the max sum rate is. The max sum rate in Fig.7 is about 10, the max sum rate in Fig.8 is about 15, and the max sum rate in Fig.9 is about 17, which is consistent with previous conclusion in Fig.4.

Above all, the two objectives result indicate the efficiency of our proposed algorithms to solve the RIS-based HBF problem with fair index and sum rate.

V. Conclusion

In this paper, we have studied an RIS-based downlink multi-user multi-antenna system in the absence of direct links between the BS and users. The BS transmits signals to users via the reflection-based RIS with limited discrete phase shifts. Considering the close coupling between channel propagation and the RIS configuration pattern selection, we have carried out an HBF scheme for sum rate maximization. Continuous digital beamforming has been performed at the BS and discrete analog beamforming has been achieved inherently at the RIS via configuration pattern selection. We solve the sum rate maximization problem with genetic algorithm, which is better than the traditional algorithm:

- *We can do multiple variables evaluation at the same time.*
- *There is no need for decoupling variables, which improve the potential accuracy.*
- *There is no need to do the approximation.*
- *It is a better way to solve NP-hard problem*

We have done some experiments and it gives a relatively good result. For comparison, the two algorithms, random BS HBF and RIS phases, the accurate BS HBF and random RIS phases are used. We simulate the sum rate versus iterations, the sum rate versus SNR, the sum rate versus RIS size N_r and the sum rate versus quantization bits. The results show the efficiency of our proposed algorithm.

We plan to add another object to the optimization problem. Besides maximizing the achievable rates of all users, we consider sum rate fairness trade-off-based resource allocation as another purpose.

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