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Joint association and beamforming optimization in reconfigurable intelligent surface-enhanced user-centric networks

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Abstract: Fully coordinated Cell-Free (CF) networks can alleviate the Inter-Cell Interference (ICI) for the cell-edge users in cellular networks. Due to the complex topology of the association between the Access Points (APs) and the users in CF networks, it is challenging to deploy CF networks in practical scenarios. In order to make CF networks feasible, we introduce User-Centric (UC) networks enabling each user served by a limited number of APs. As a low-cost and energy-efficient technology, Reconfigurable Intelligent Surface (RIS) can be embedded in UC networks to further improve the system performance. First, we provide a brief survey on the prior works in UC networks for clear comprehension. Then, we formulate a Spectral Efficiency (SE) maximization problem for RIS-enhanced UC networks. For solving the non-convex problem, we divide it into three subproblems and propose a joint optimization framework for optimizing AP-user association, active beamforming of multiple antennas at the APs, and the passive beamforming of the RIS. Besides, a channel gain based association method coupled with the design of RIS is proposed to construct a dynamic and efficient association. The subproblems about optimizing active and passive beamforming are solved with the fractional programming. Simulation results show that the proposed joint optimization framework for RIS-enhanced UC networks can obtain good SE compared with other benchmark schemes.

Key words: User-Centric (UC) networks; Reconfigurable Intelligent Surface (RIS); association optimization

1 Introduction

As the brief evolution process of cellular networks is shown in Ref. [1], the first cellular commercial system came into being in the late 1970s and early 1980s. The well-known conventional model of the cellular network is composed of several hexagonal cells, where a Base Station (BS) or Access Point (AP) is introduced in each cell[2]. Actually, it is an AP-centric network paradigm for the definition of each cell deriving from the coverage of the AP. The users at the cell edge confront serious Inter-Cell Interference (ICI) in AP-centric network, which becomes a bottleneck for the enhancement of the system capacity.

As a promising network paradigm to eliminate the ICI of cell-edge users in cell-centric networks, Cell-Free (CF) network was widely studied. This new network architecture was introduced in Ref. [3], where all APs were coordinated jointly to serve all users with the same time-frequency resource. In Ref. [4], CF network was also called inter-cell coordination, which has been shown to be an effective idea to improve the capacity compared with conventional cellular networks. As proved in Ref. [5], CF massive MIMO

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systems can outperform small-cell systems in terms of throughput. Nonetheless, CF systems require more backhaul. In Ref. [6], authors have illustrated that fronthaul/backhaul links and signaling overhead would increase dramatically with the expansion of the network scale, e.g., the numbers of APs and users. Especially, when a large number of APs and massive users have been deployed in B5G/6G era[7], fully coordinated AP-user association will make the network overwhelmed with high deploying complexity. Thus, fully coordinated CF network is challenging to be deployed in practical scenarios.

A heuristic idea to make CF network feasible in deployment is to limit the number of inter-coordinated APs, which is introduced as User-Centric (UC) network paradigm in Ref. [8]. In UC network paradigm, each user is served by a limited number of APs while the network units are divided by users. Considering the connecting topology between APs and users, the critical problem in UC network is how to design an effective and lightweight AP-user association. As it is NP-hard in large-scale networks, this problem becomes a huge challenge.

The specific examples of cellular network, fully coordinated CF network and UC network are shown in Fig. 1. In Table 1, we summarize some characteristics of these networks. In general, the cellular network in Fig. 1a has ICI problems and low backhaul/fronthaul burden. The fully coordinated CF network in Fig. 1b and the UC network in Fig. 1c have eliminated ICI problem, but the former has heavier backhaul/fronthaul burden. In fact, since the association can be optimized in UC network, its backhaul/fronthaul burden is adjustable.

In the UC network, due to the complexity of association problem itself, the greatest difficulty is to consider the joint optimization of association and resource allocation. In order to construct a lightweight and energy-saving UC network, an emerging technique called Reconfigurable Intelligent Surface (RIS) can be utilized to facilitate UC networks. RIS is composed of an array of passive reflecting elements made of metal materials, which can manipulate the wireless propagation environment by adjusting the coefficients of the reflecting elements[9, 10]. Although the trivial power cost of RIS in working mode exists, the passive beamforming of RIS can improve Signal-to-Noise Ratio (SNR) significantly, providing an obvious gain on the energy efficiency of the system[11]. Therefore, the requirements about flexible association and low power in UC network could be satisfied by the deployment of the RIS. Usually, static AP-user association assigning each user with a limited number of APs based on channel strength can be easily established, which only depends on the initial phase of RIS and the locations of APs and users.

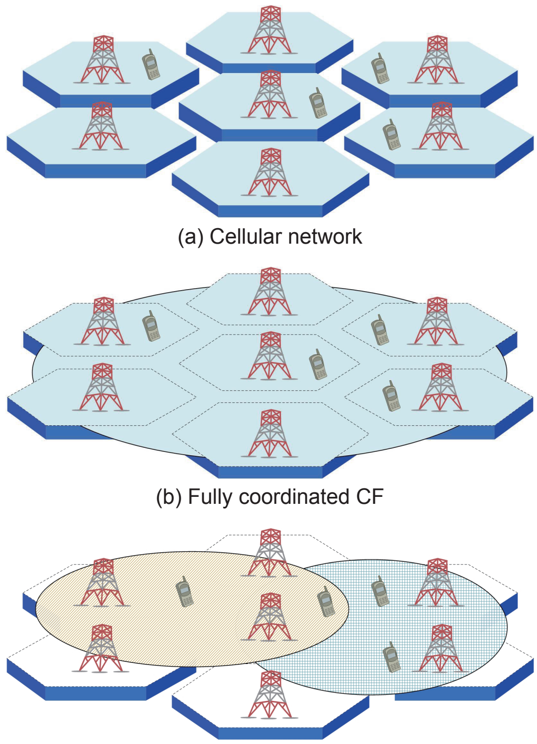

Fig. 1 Network paradigms.

Table 1 Comparison among different networks.

Network	ICI problem	Network unit	Backhaul/fronthaul burden
Cellular network	√	AP-centric network unit	Low
Fully coordinated CF network	×	Whole network	High
User-centric network	×	User-centric network unit	Adjustable

In this paper, a dynamic AP-user association called channel gain based (h-based) method is considered, which is coupled with the design of coefficients of RIS.

The h -based association provides a more flexible scheduling in the association. Besides, the weighted sum rate of all the users can be maximized by the joint optimization of active beamforming or transmit precoding of the multiple antennas at the APs and the passive beamforming of the RIS. Meanwhile, theoretical analysis and experimental results show that the proposed dynamic AP-user association method does not impose too much burden on the complexity of the overall algorithm.

The remaining sections of this paper are organized as follows. Section 2 performs a survey on the prior works at three critical aspects in UC networks. Section 3 presents the system model and the formulated problem about joint association and beamforming in RIS-aided UC networks. Section 4 illustrates the proposed joint optimization framework about AP-user association, the transmit precoding at the APs, and the reflecting coefficients at the RIS. Section 5 shows the simulation results and discussions. Section 6 presents some research directions in the future. Finally, Section 7 draws the conclusion.

2 Prior works in UC networks

It is worth noting that deploying UC networks in practical communication scenarios should overcome difficulties at many aspects, e.g., AP-user association, resource allocation, etc. Some researchers put a lot of efforts to improve the performance of UC networks with the emerging technologies, e.g., massive MIMO[12]. To obtain a thorough view of technical challenges on UC networks, a brief description of some critical issues on investigating UC networks are shown as follows.

2.1 AP-user association

Actually, the essence of UC networks is to realize the trade-off between the complexity of establishing AP-user association and the performance metrics, e.g., Spectral Efficiency (SE) or Energy Efficiency (EE). From an intuitive perspective, the dense connecting topology of the AP-user association may provide more degrees of freedom in spatial domain. In Ref. [8], each AP sorts all users' channel coefficients and tries to serve users with the strongest channel. Another heuristic association idea is that each user connects to the APs which can provide the maximum signal power for it[13]. A user-centric Dynamic Cooperation Clustering (DCC) framework was investigated in Ref. [12], as well as a channel-based AP-user association method developed to form clusters. All the above association methods are designed to maximize the performance gain of the system. Thus, utility-based clustering can be used to describe them. When the RIS is introduced into the UC networks, AP-user association problem becomes more complicated for high-dimension cascaded channels including AP-RIS and RIS-user components. In Ref. [14], the AP-user association was simplified and disassembled as RIS-user matching subproblem, which was solved by Linear Conic Relaxation (LCR) based method. To the best of our knowledge, the AP-user association in RIS-aided UC network has not been considered from the view of the entire cascaded channel, which is the basic motivation of this paper.

2.2 Resource allocation

Usually, the resource in UC networks includes the power of APs, the transmit precoding of the multiple antennas at the APs, the subcarrier allocation in wideband system, etc. Although appropriate resource allocation in UC networks is helpful to improve the performance metrics, it becomes intractable in large-scale networks. The purpose of resource allocation is to optimize some performance metrics of the communication systems, which usually include SE, EE, latency, fairness, etc. The training resource allocation for channel estimation in UC cooperation networks is solved by a graph-theoretic approach optimally and a low-complexity algorithm sub-optimally for the large-scale networks, respectively[15]. Besides, two distributed downlink resource allocation algorithms was proposed to optimize a hybrid quality of service metric with user scheduling, beamforming, and power control in UC MIMO networks, which shows the Central Unit (CU) distributed system providing 1.3- to 1.8-fold network throughput compared to the Distributed Unit (DU) distributed system[16]. In addition, the proportional-fair resource allocation including multiple time slots allocation and precoding design in UC networks was formulated as the weighted sum-rate maximization problems, which were solved by a two-stage heuristic scheme and a modularity-based user grouping algorithm[17]. Scalable precoding schemes were used for beamforming under UC-DCC framework, promoting the SE of the system in Ref. [12]. A Block Coordinate Descent (BCD) based joint AP clustering and beamformer optimization algorithm was proposed to solve the formulated problem about maximizing the rate-dependent utility function in Ref. [14].

Due to the energy-saving characteristic of RIS, it has been embedded in fully coordinated CF network to replace some inefficient APs in Ref. [18]. In Ref. [19], the resource allocation problem of joint design of reflection matrix of RIS and power control at APs to maximize energy efficiency was posed in RIS-aided UC networks.

2.3 Channel estimation

Compared with the cellular networks, the fully coordinated CF networks and UC networks have more complex connecting topology between APs and users, which brings a huge challenge to the estimation of Channel State Information (CSI). The two-stage approach based on the vector approximate message passing algorithm and linear minimum mean square error method was proposed to detect the random activities of devices and estimate their channel states for the devices of Internet of Thing in UC networks with massive random access in Ref. [20]. Besides, the blind channel estimation method for UC MIMO networks was investigated in Ref. [21], which provided lower normalized mean-square error compared with statistical CSI and good performance in the presence of pilot contamination. In Ref. [22], the scalable pilot assignment algorithm considering the eigenspace of channel vectors was adopted to minimize the sum pilot contamination caused by all the serving APs in UC MIMO networks. Considering the high computational complexity of exploiting an accurate estimation of CSI for the massive antennas at APs and the large bandwidth at mmWave in UC networks, the fast and flexible denoising convolutional neural networks were embedded into the channel estimator[23].

When the RIS is introduced into the UC networks, the burden of channel estimation becomes heavier for the added task of estimation about the cascaded channels. Reducing the pilot overhead moderately, the proposed two-timescale channel estimation for RIS-aided wireless communications[24] is also suitable for the RIS-aided UC networks. Since RIS can enhance the system performance via manipulating the wireless environments, a deep understanding of the CSI measurement lays a prior foundation for joint optimization of association and beamforming in RIS-aided UC networks.

3 System model

As shown in Fig. 2, a downlink transmission of RIS-enhanced UC network is investigated in this work. There are B multi-antenna APs with L antennas, K single-antenna users, and an RIS with N elements deployed in this scenario. The index sets of APs, the antennas of each AP, users, and the elements of RIS are denoted by $\mathcal{B}=\{1,2,\ldots,B\}$, $\mathcal{L}=\{1,2,\ldots,L\}$, $\mathcal{K}=\{1,2,\ldots,K\}$, and $\mathcal{N}=\{1,2,\ldots,N\}$, respectively.

In UC network, each AP will only serve part of the users. Signal transmitted by the b-th AP is

$$\boldsymbol{x}_b=\sum_{k=1}^{K} c_{b,k}\boldsymbol{w}_{b,k}s_k \tag{1}$$

where s_k means the sending symbol for the k-th user. $\boldsymbol{w}_{b,k}\in\mathbf{C}^{L\times1}$ represents the beamforming vector of the b-th AP for the k-th user, and L is the number of antennas

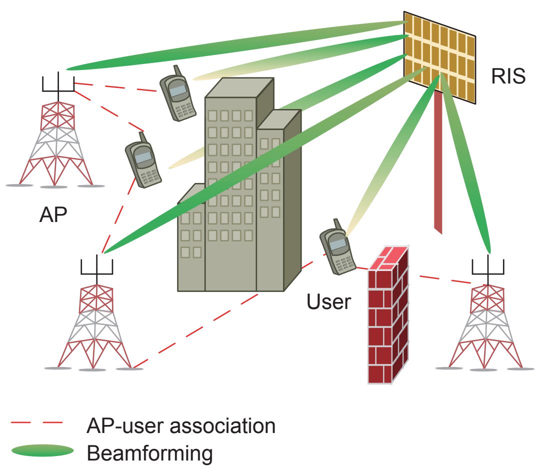

Fig. 2 An RIS-aided UC network.

at each AP. When the b-th AP chooses to serve the k-th user, $c_{b,k}=1$ holds, otherwise $c_{b,k}=0$.

The effective channel from each AP to a user can be expressed as

$$\boldsymbol{h}_{b,k}^{\mathrm{H}}=\boldsymbol{d}_{b,k}^{\mathrm{H}}+\boldsymbol{f}_{\mathrm{r},k}^{\mathrm{H}}\boldsymbol{\Theta}^{\mathrm{H}}\boldsymbol{G}_{b,\mathrm{r}} \tag{2}$$

where $\boldsymbol{d}_{b,k}\in\mathbf{C}^{L\times 1}$ is the channel of the direct link from the b-th AP to the k-th user, which can be modeled as Rayleigh fading[25]. $\boldsymbol{G}_{b,\mathrm{r}}\in\mathbf{C}^{N\times L}$ and $\boldsymbol{f}_{\mathrm{r},k}^{H}\in\mathbf{C}^{1\times N}$ are the channels in the cascade links from the b-th AP to RIS and RIS to the k-th user, respectively, which conform to Rician fading. CSI is assumed to be perfectly known in our system. We define $\boldsymbol{\Theta}=\mathrm{diag}(\theta_{\mathrm{r},1},\theta_{\mathrm{r},2},\ldots,\theta_{\mathrm{r},N})$ as matrix of reflection coefficients of RIS. Each reflection element is $\theta_{\mathrm{r},n}=\kappa_n\mathrm{e}^{\mathrm{j}\phi_n}(n\in\mathcal{N})$, where $\phi_n\in[0,2\pi)$ is the phase shift coefficient and κ_n represents amplitude part.

The received signal of the k-th user is

$$y_k=\sum_{b=1}^{B}\boldsymbol{h}_{b,k}^{\mathrm{H}}c_{b,k}\boldsymbol{w}_{b,k}s_k+\sum_{b=1}^{B}\sum_{j=1,j\neq k}^{K}\boldsymbol{h}_{b,k}^{\mathrm{H}}c_{b,j}\boldsymbol{w}_{b,j}s_j+z_k \tag{3}$$

The additive white Gaussian noise for the k-th user is an independent and identically distributed circular symmetric complex Gaussian random variable with zero mean and the variance σ_k^2, expressed as $z_k\sim\mathcal{CN}\left(0,\sigma_k^2\right)$. The decoding Signal to Interference plus Noise Ratio (SINR) for the k-th user can be formulated as

$$\gamma_k=\frac{\left|\sum_{b=1}^{B}\boldsymbol{h}_{b,k}^{\mathrm{H}}c_{b,k}\boldsymbol{w}_{b,k}\right|^2}{\sum_{j=1,j\neq k}^{K}\left|\sum_{b=1}^{B}\boldsymbol{h}_{b,k}^{\mathrm{H}}c_{b,j}\boldsymbol{w}_{b,j}\right|^2+\sigma_k^2} \tag{4}$$

The problem about maximization of SE can be expressed as

$$(\mathrm{P}_1)\quad \max_{\boldsymbol{C},\boldsymbol{W},\boldsymbol{\Theta}}\quad f(\boldsymbol{C},\boldsymbol{W},\boldsymbol{\Theta})=\sum_{k=1}^{K}\eta_k\log_2(1+\gamma_k) \tag{5}$$

$$\text{s.t.,}\quad \sum_{k=1}^{K}c_{b,k}\leqslant M,\ b\in\mathcal{B} \tag{6}$$

$$\sum_{k=1}^{K}\|c_{b,k}\boldsymbol{w}_{b,k}\|^2\leqslant P_{\max},\ b\in\mathcal{B} \tag{7}$$

$$\|\theta_{r,n}\|^2\leqslant 1,\ n\in\mathcal{N} \tag{8}$$

where $\boldsymbol{C}$ and $\boldsymbol{W}$ are the association matrix and the active beamforming matrix composed of the elements $\{c_{b,k}\}$ and $\{\boldsymbol{w}_{b,k}\}$, respectively. Weighted factor of the k-th user is η_k, which can be set as $1/K$. Formulas (6), (7), and (8) denote maximum number constraint of served users per AP, maximum power constraint of an AP, and the constraint of per reflection element of RIS, respectively.

Through joint optimizing $\boldsymbol{C}$, $\boldsymbol{W}$, and $\boldsymbol{\Theta}$, we can maximize SE of the whole system. However, the non-convexity of objective function in P1 and constraint of Formula (6) make it difficult to find an optimal solution for this problem. Next, fractional programming technique, h-based association, and joint optimization are used to obtain a sub-optimal solution efficiently.

4 Joint optimization framework

Firstly, Lagrangian Dual Transform Technique (LDTT) is used to transform original objective function in P1 into

$$f_1(\boldsymbol{C},\boldsymbol{W},\boldsymbol{\Theta},\boldsymbol{\alpha})=\sum_{k=1}^{K}\eta_k\log_2(1+\alpha_k)-\sum_{k=1}^{K}\eta_k\alpha_k+\sum_{k=1}^{K}\frac{\eta_k(1+\alpha_k)\gamma_k}{1+\gamma_k} \tag{9}$$

The intermediate variable for receiving SINR is α_k and $\boldsymbol{\alpha}=[\alpha_1,\alpha_2,\ldots,\alpha_K]^{\mathrm{T}}$. When $\boldsymbol{C}$, $\boldsymbol{W}$, and $\boldsymbol{\Theta}$ are fixed, we have the optimal $\alpha_k^{\mathrm{o}}=\gamma_k$. Then, with $\boldsymbol{\alpha}$ fixed, $f_1(\boldsymbol{C},\boldsymbol{W},\boldsymbol{\Theta},\boldsymbol{\alpha})$ can be transformed into

$$f_1^{'}(\boldsymbol{C},\boldsymbol{W},\boldsymbol{\Theta},\boldsymbol{\alpha})=\sum_{k=1}^{K}\frac{\omega_k\gamma_k}{1+\gamma_k} \tag{10}$$

where $\omega_k=\eta_k(1+\alpha_k)$. Finally, the new problem P1$'$ can be obtained as

$$\begin{aligned}&(\mathrm{P1}')\quad \max_{\boldsymbol{C},\boldsymbol{W},\boldsymbol{\Theta},\boldsymbol{\alpha}}\quad f_1^{'}(\boldsymbol{C},\boldsymbol{W},\boldsymbol{\Theta},\boldsymbol{\alpha}),\\&\text{s.t.,}\quad \text{Formulas (6)}-(8).\end{aligned}$$

The joint alternating optimization framework is shown in Algorithm 1, where $\boldsymbol{C}$, $\boldsymbol{W}$, and $\boldsymbol{\Theta}$ are optimized, respectively. This process continues until the objective function $f(\boldsymbol{C},\boldsymbol{W},\boldsymbol{\Theta})$ in P1 reaches a stable value. In the following section, process of optimization of three subproblems is investigated, specifically. Algorithm 1 will converge to a final state, because the

Algorithm 1 Alternating optimization for P1

Input: $\boldsymbol{W}^{(0)}$ and $\boldsymbol{\Theta}^{(0)}$

1: **while:** $|f^{(t)}(\boldsymbol{C},\boldsymbol{W},\boldsymbol{\Theta}) - f^{(t-1)}(\boldsymbol{C},\boldsymbol{W},\boldsymbol{\Theta})| < \delta$ **do**

2: Update $\boldsymbol{C}^{(t)}$ by the proposed Algorithm 2

3: Update intermediate SINR $\boldsymbol{\alpha}^{(t)}$ by $\alpha_k^{\circ} = \gamma_k$

4: Update $\boldsymbol{\beta}^{(t)}$, obtain $\boldsymbol{W}^{(t)}$ by solving P2

5: Update $\boldsymbol{\epsilon}^{(t)}$, obtain $\boldsymbol{\Theta}^{(t)}$ by solving P3

6: **end while**

Output: $\boldsymbol{C}^{(t)}$, $\boldsymbol{W}^{(t)}$, and $\boldsymbol{\Theta}^{(t)}$.

Note: Algorithm 2 is designed in Section 4.1. P2 and P3 are introduced in Sections 4.2 and 4.3, respectively.

possible states of matrix $\boldsymbol{C}$ are finite. Besides, the other two subproblems can be transformed into convex problems. We define I_a, I_w, and I_θ as the numbers of the iterations for solving AP-user association, the active beamforming of the multiple antennas at the AP, and passive beamforming of the RIS, respectively. Thus, $O\left(I_a(I_w B^2 K^2 + I_\theta N^2)\right)$ can be used to express the computational complexity of Algorithm 1.

4.1 User association

In this part, our purpose is to build a lightweight effective association. The core principle is that the AP-user associations with strong channel strengths tend to be activated in priority, while those with weak channel strength are likely to be disconnected.

In the RIS-enhanced systems, the effective channel $\boldsymbol{h}_{b,k}$ is expressed as Eq. (2) where the reflection coefficients of RIS $\boldsymbol{\Theta}$ are involved. Therefore, we propose the h-based association method which is coupled with $\boldsymbol{\Theta}$. Its specific process is summarized as Algorithm 2, in which the optimization of association $\boldsymbol{C}$ and $\boldsymbol{\Theta}$ will be coupled. With $\boldsymbol{C}$ fixed, the optimal $\boldsymbol{\Theta}$ can be obtained. On the other hand, the changing of $\boldsymbol{\Theta}$ will lead to new effective channel $\{\boldsymbol{h}_{b,k}\}$, which derives a new optimal $\boldsymbol{C}$ in the process of Algorithm 1 with h-based association. This process will continue in this coupled manner until the objective function $f(\boldsymbol{C},\boldsymbol{W},\boldsymbol{\Theta})$ in P1 converges.

Algorithm 2 h-based association

Input: $\boldsymbol{\Theta}$

1: Calculate $\{\boldsymbol{h}_{b,k}\}$ based on $\boldsymbol{\Theta}$

2: **for** $k = 1 : K$ **do**

3: Sort all APs channel coefficients in descending order

4: Pick the strongest channel and let corresponding $c_{b,k} = 1$, otherwise $c_{b,k} = 0$

5: **end for**

Output: $\boldsymbol{C}$

In the h-based approach, the association process is based on users' effective channel coefficients $\{\boldsymbol{h}_{b,k}\}$. With $\boldsymbol{\Theta}$ fixed, we can calculate the effective channel coefficients $\{\boldsymbol{h}_{b,k}\}$. For the k-th user, it will sort these channel coefficients in descending order and only connects to APs with the strongest effective channels. The computational complexity of Algorithm 2 is $O(BK)$.

4.2 Active beamforming at the AP

With $\boldsymbol{C}$, $\boldsymbol{\Theta}$, and α fixed, the original problem P1 shifts into

$$\begin{aligned} &(\text{P2}) \quad \max_{\boldsymbol{W}} \quad f_2(\boldsymbol{W}), \\ &\text{s.t.,} \quad \text{Formula (7)}, \end{aligned}$$

where

$$f_2(\boldsymbol{W}) = \sum_{k=1}^{K} \frac{\omega_k \left| \sum_{b=1}^{B} \boldsymbol{h}_{b,k}^{\mathrm{H}} c_{b,k} \boldsymbol{w}_{b,k} \right|^2}{\sum_{j=1}^{K} \left| \sum_{b=1}^{B} \boldsymbol{h}_{b,k}^{\mathrm{H}} c_{b,j} \boldsymbol{w}_{b,j} \right|^2 + \sigma_k^2} \tag{11}$$

Utilizing the quadratic transform[26], the objective function of P2 can be transformed into

$$\begin{aligned} f_2{}'(\boldsymbol{W},\boldsymbol{\beta}) = &\sum_{k=1}^{K} 2\sqrt{\omega_k} \mathrm{Re}\{\beta_k^* \sum_{b=1}^{B} \boldsymbol{h}_{b,k}^{\mathrm{H}} c_{b,k} \boldsymbol{w}_{b,k}\} - \\ &\sum_{k=1}^{K} |\beta_k|^2 \left(\sum_{j=1}^{K} \left| \sum_{b=1}^{B} \boldsymbol{h}_{b,k}^{\mathrm{H}} c_{b,j} \boldsymbol{w}_{b,j} \right|^2 + \sigma_k^2 \right) \end{aligned} \tag{12}$$

where $\boldsymbol{\beta} = [\beta_1, \beta_2, \ldots, \beta_K]^{\mathrm{T}}$ and the optimal β_k° is given by $\partial f_2' / \partial \beta_k = 0$, shown in the following:

$$\beta_k^{\circ} = \frac{\sqrt{\omega_k} \sum_{b=1}^{B} \boldsymbol{h}_{b,k}^{\mathrm{H}} c_{b,k} \boldsymbol{w}_{b,k}}{\sum_{j=1}^{K} \left| \sum_{b=1}^{B} \boldsymbol{h}_{b,k}^{\mathrm{H}} c_{b,j} \boldsymbol{w}_{b,j} \right|^2 + \sigma_k^2} \tag{13}$$

Finally, substituting β_k° into $f_2'(\boldsymbol{W},\boldsymbol{\beta})$, the subproblem P2 is equivalent to

$$\begin{aligned} &(\text{P2}') \quad \max_{\boldsymbol{W}} \quad f_2'(\boldsymbol{W}, \boldsymbol{\beta}^{\circ}), \\ &\text{s.t.,} \quad \text{Formula (7)}, \end{aligned}$$

where $f_2'(\boldsymbol{W}, \boldsymbol{\beta}^{\circ})$ is a quadratic concave function of $\boldsymbol{W}$

and Formula (7) is a convex set. Therefore, P2′ is a convex problem which can be solved by a standard convex optimization tool[27] directly.

4.3 Passive beamforming of the RIS

Define some variables for solving the passive beamforming problem, which are shown as

$$l_{b,i,k}=\boldsymbol{d}_{b,k}^{\mathrm{H}}c_{b,i}\boldsymbol{w}_{b,i} \tag{14}$$

$$\boldsymbol{\theta}_{\mathrm{r}}^{\mathrm{H}}=[\theta_{\mathrm{r},1},\theta_{\mathrm{r},2},\ldots,\theta_{\mathrm{r},N}]^{\mathrm{H}} \tag{15}$$

$$\boldsymbol{a}_{b,i,k}=\mathrm{diag}(\boldsymbol{f}_{\mathrm{r},k}^{\mathrm{H}})\boldsymbol{G}_{b,\mathrm{r}}c_{b,i}\boldsymbol{w}_{b,i} \tag{16}$$

With $\boldsymbol{C}$, $\boldsymbol{W}$, and $\boldsymbol{\alpha}$ fixed, the objective function in P1 can be equivalently given by

$$f_3(\boldsymbol{\theta}_{\mathrm{r}})=\sum_{k=1}^{k}\frac{\omega_k\left|\sum_{b=1}^{B}\left(l_{b,k,k}+\boldsymbol{\theta}_{\mathrm{r}}^{\mathrm{H}}\boldsymbol{a}_{b,k,k}\right)\right|^2}{\sum_{i=1}^{K}\left|\sum_{b=1}^{B}\left(l_{b,i,k}+\boldsymbol{\theta}_{\mathrm{r}}^{\mathrm{H}}\boldsymbol{a}_{b,i,k}\right)\right|^2+\sigma_k^2} \tag{17}$$

Since Eq. (17) is still a complex multiple ratio term, we can transform it into Eq. (18) by the quadratic transform,

$$f_3'(\boldsymbol{\theta}_{\mathrm{r}},\boldsymbol{\xi})=\sum_{k=1}^{K}2\sqrt{\omega_k}\mathrm{Re}\left\{\xi_k^*(\boldsymbol{\theta}_{\mathrm{r}}^{\mathrm{H}}\sum_{b=1}^{B}\boldsymbol{a}_{b,k,k}+\sum_{b=1}^{B}l_{b,k,k})\right\}-\sum_{k=1}^{K}|\xi_k|^2\left(\sum_{i=1}^{K}\left|\sum_{b=1}^{B}(l_{b,i,k}+\boldsymbol{\theta}_{\mathrm{r}}^{\mathrm{H}}\boldsymbol{a}_{b,i,k})\right|^2+\sigma_k^2\right) \tag{18}$$

where the auxiliary variable $\boldsymbol{\xi}=[\xi_1,\xi_2,\ldots,\xi_K]^{\mathrm{T}}$ and the optimal ξ_k° for a fixed $\boldsymbol{\theta}_{\mathrm{r}}^{\mathrm{H}}$ can be obtained by $\partial f_3'/\partial\xi_k=0$, shown in the following:

$$\xi_k^{\circ}=\frac{\sqrt{\omega_k}\left(\sum_{b=1}^{B}l_{b,k,k}+\boldsymbol{\theta}_{\mathrm{r}}^{\mathrm{H}}\sum_{b=1}^{B}\boldsymbol{a}_{b,k,k}\right)}{\sum_{i=1}^{K}\left|\sum_{b=1}^{B}l_{b,i,k}+\boldsymbol{\theta}_{\mathrm{r}}^{\mathrm{H}}\sum_{b=1}^{B}\boldsymbol{a}_{b,i,k}\right|^2+\sigma_k^2} \tag{19}$$

By taking Eq. (19) into Eq. (18), the subproblem of optimization on reflection coefficients is

$$\begin{aligned}&(\mathrm{P3})\quad \max_{\boldsymbol{\theta}_{\mathrm{r}}}\quad f_3'(\boldsymbol{\theta}_{\mathrm{r}},\boldsymbol{\xi}^{\circ}),\\&\text{s.t.,}\quad \text{Formula (8)}.\end{aligned}$$

$f_3'(\boldsymbol{\theta}_{\mathrm{r}},\boldsymbol{\xi}^{\circ})$ is a quadratic concave function of $\boldsymbol{\theta}_{\mathrm{r}}$, and the constraint Formula (8) is a convex set. Therefore, P3 is a convex problem which can be solved by a standard convex optimization tool[27].

5 Simulation results and discussion

In our simulation scenario, four APs are uniformly deployed on a semicircle with a radius of 100 meters and center coordinate of (100 m, 0 m). Users are randomly distributed in a circle with a radius of 2 m at the center of the semicircle. An RIS of Uniform Linear Array (ULA) is deployed closely to the users at (100 m, −2 m). There are mainly two simulation cases, where the number of users is $K=4$ or $K=8$, respectively. The maximum number of connected users of each AP is limited with $M=3$ or $M=6$, respectively. To clarify clearly, we introduce Table 2 to illustrate the different schemes, where NoRIS means the case without RIS deployed.

Weighted Sum Rate (WSR) with respect to each AP's maximum power $P_{\max}$ is illustrated in Fig. 3. In the two specific simulation scenarios, we assume that each AP does not have the ability to serve all users at the same time. Usually, the RIS-enhanced system has a better performance gain than that of NoRIS, which prove that RIS plays a leading role in guaranteeing brilliant SE

Table 2 Simulation schemes.

Abbreviation	Description of scheme
RIS-AC	$\boldsymbol{W}$ and $\boldsymbol{\Theta}$ optimization algorithm with all connected CF association (AC, i.e., $c_{b,k}=1$, $\forall b\in\mathcal{B}$ and $\forall k\in\mathcal{K}$)
RIS-HA	Alternating iterative optimization algorithm with h-based association (HA)
RIS-RA	Alternating iterative optimization algorithm with random association (RA)
NoRIS-HA	Optimization of $\boldsymbol{W}$ in NoRIS h-based association system

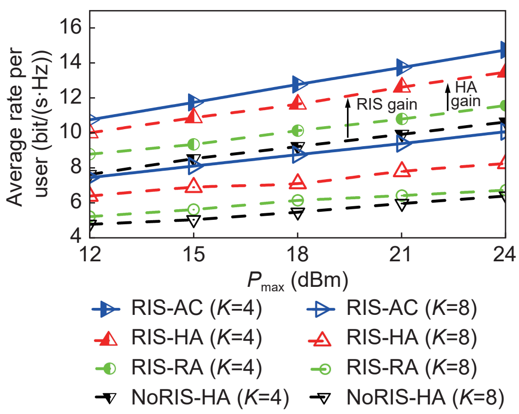

Fig. 3 Average rate per user versus $P_{\max}$ with $N=30$ and $L=2$.

performance for users. With the increasing of $P_{\max}$, the improvement of WSR of RIS-RA is very slight compared with that of RIS-HA. This is because Random Association (RA) may disconnect the AP-user links which have good channel coefficients. In this case, even if $P_{\max}$ increases, it can not be allocated on suitable links to achieve a considerable performance gain of WSR. This is the reason why $\boldsymbol{C}$ and $\boldsymbol{W}$ need to be jointly designed. SE performance of RIS-HA coincides with that of RIS-AC schemes, which shows the effectiveness of h-based association.

As expected, WSR of all algorithms increases as the elements of RIS increase in Fig. 4. Similarly, the performance of RIS-HA approach approximates to that of RIS-AC very well. The power consumption model of our system is defined as Eq. (20) based on the network power consumption model in Ref. [11],

$$P_{\mathrm{S}} = \sum_{b=1}^{B}\sum_{k=1}^{K}\|\boldsymbol{w}_{b,k}\|^2 + \sum_{k=1}^{K} p_k + p_{\mathrm{r}} + B\cdot P_{\mathrm{AP}} \tag{20}$$

The power consumption of the k-th user is denoted as $p_k = 123 + 1169 B_{\mathrm{a}}/B$ mW[28], where B_{a} is the number of the active association between the k-th user and the APs. The power consumption of RIS is p_{r}. The hardware-dissipated power of AP P_{AP} can be approximated by a constant power offset 9 dBW.

In Fig. 5, as the number of elements of RIS increases, RIS-HA has saved more energy than RIS-AC. Comparing the results of 4 users and 8 users, energy performance of RIS-HA algorithm is improved better than that of RIS-AC, with the number of users $K = 8$. It can be explained that RIS-HA algorithm turns

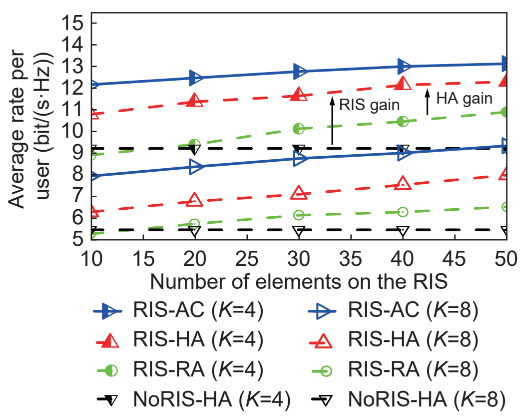

Fig. 4 Average rate per user versus N with $P_{\max}$ = 18 dBm and L= 2.

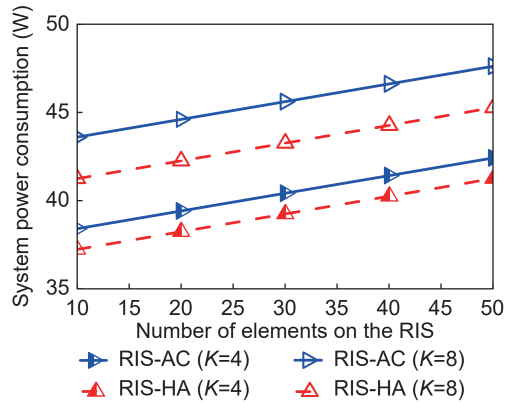

Fig. 5 System power consumption versus N with $P_{\max}$ = 18 dBm and L = 2.

off more inefficient association bits in order to meet the upper bound of the AP's association ability, with $K = 8$ and $M = 6$. According to the power consumption model in Eq. (20), AP-user association is more lightweight in h-based approach where the power consumption of each user p_k can be saved.

As shown in Fig. 6, within a certain range, the SE of the system will be improved with the increase of the number of antennas of each AP. This SE improvement can be attributed to the increased diversity gain in multi-antenna transmission system.

In Fig. 7, the relationship between the number of iterations and WSR in 100 channel realizations is shown, with the number of elements of RIS N = 10, maximum power of each AP $P_{\max}$= 18 dBm, and the number of antennas per AP L = 2. We can observe that the WSR performance of both RIS-AC and RIS-HA converges after about 5 iterations, which is consistent with the computational complexity analysis in the previous part. In the 100 channel simulations, the

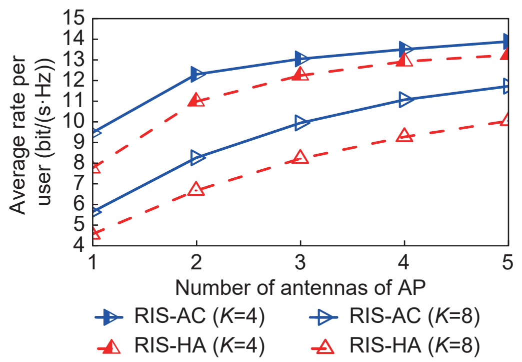

Fig. 6 Average rate per user versus the number of antennas of each AP with $P_{\max}$ = 18 dBm and N= 10.

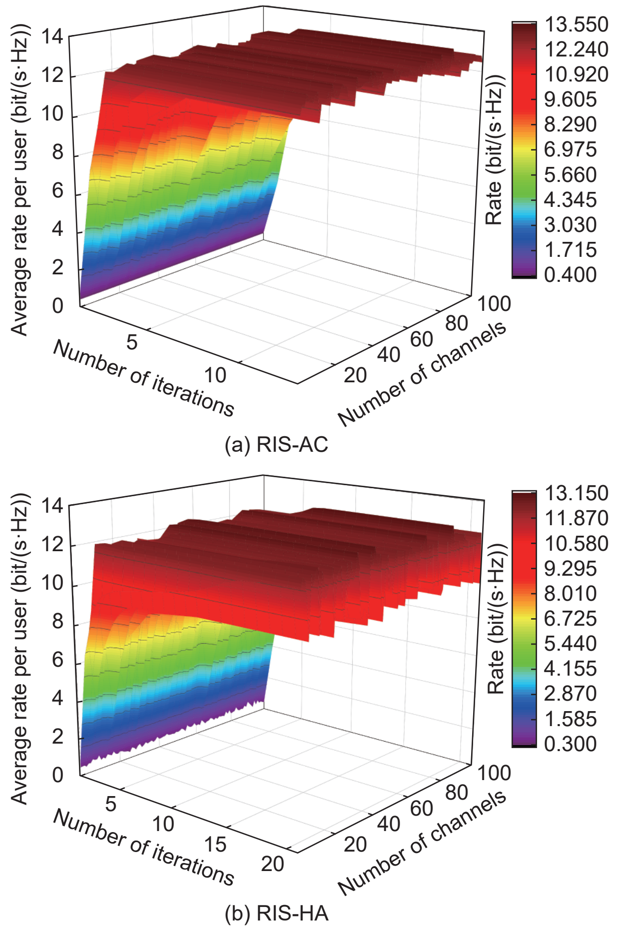

Fig. 7 Average rate per user versus the number of iterations in 100 channel realizations with independent small-scale fading, where $P_{\max}$ = 18 dBm, L = 2, and N = 10.

variance of the final state of RIS-HA algorithm is greater than that of RIS-AC. Due to the strong correlation between AP-user association and channel state in RIS-HA, the association has impact on the final state of convergence in each iteration.

6 Future research directions

6.1 Deployments of multiple types of RISs

Except for the passive RIS, active RIS[29] and Simultaneously Transmitting And Reflecting Surface (STARS)[30] are also proposed recently for combating the multiplicative fading effect and increasing the degrees of freedom in spatial domain, respectively. These advantages of active RIS and STARS can improve the capacity and coverage of the UC networks significantly. Therefore, the hybrid deployments of passive RIS, active RIS, and STARS in UC networks can be a promising research field. It is worth noting that the hybrid deployments of RIS include the geometric position of the RISs and the design of the reflecting coefficients of RIS. Besides, the AP-user association including the AP-RIS links and RIS-user links may also need to be reconstructed for maximizing the capacity performance of the UC networks.

6.2 Deep learning-assisted dynamic management

As the channel estimation based on deep learning in UC networks was verified in Ref. [23], many tasks, e.g., the storing and acquiring of the CSI data, subcarrier allocation, and transmit precoding design in UC networks can be jointly managed by the deep learning algorithms. Usually, these tasks are coupled in enhancing the performance metrics of the UC networks, which is difficult to solve the problem by optimizing all the tasks analytically. Meanwhile, deep learning algorithms show the advantages on managing multiple tasks simultaneously based on the data and training. The central processing unit connecting the coordinated APs with the backhaul links provides a good opportunity to deploy the entity of deep learning algorithms to manage the AP-user association, bandwidth allocation, power control, and RIS configurations. Besides, the design of the managing system based on deep learning should be flexible, whose size can be adjusted in accordance with the scale of the UC networks.

7 Conclusion

In this paper, we investigate evolution process of network paradigms and prior works in UC networks. A joint optimization problem about AP-user association, beamforming of APs and reflection coefficients on RIS is formulated to maximize WSR under RIS-enhanced UC networks. To tackle this problem, an alternating iterative optimization framework is proposed to decouple original problem into three subproblems. Moreover, a dynamic AP-user association can be effectively reconstructed by RIS through changing the wireless channels which are critical factor for the determination of AP-user association. Simulation results show that RIS-enhanced h-based UC method realizes good WSR with a low-cost approach, which is a promising solution for the deployment of UC networks.

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