# Cooperative Distributed Beamforming Design for Multi-RIS Aided Cell-Free Systems

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**Abstract:** Cell-free systems significantly improve network capacity by enabling joint user service without cell boundaries, eliminating inter-cell interference. However, to satisfy further capacity demands, it leads to high-cost problems of both hardware and power consumption. In this paper, we investigate multiple reconfigurable intelligent surfaces (RISs) aided cell-free systems where RISs are introduced to improve spectrum efficiency in an energy-efficient way. To overcome the centralized high complexity and avoid frequent information exchanges, a cooperative distributed beamforming design is proposed to maximize the weighted sum-rate performance. In particular, the alternating optimization method is utilized with the distributed closed-form solution of active beamforming being derived locally at access points, and phase shifts are obtained centrally based on the Riemannian conjugate gradient (RCG) manifold method. Simulation results verify the effectiveness of the proposed design whose performance is comparable to the centralized scheme and show great superiority of the RISs-aided system over the conventional cellular and cell-free system.

**Keywords:** cell-free systems; reconfigurable intelligent surface; cooperative distributed beamforming; Riemannian conjugate gradient

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## 1 Introduction

To satisfy the ever-increasing demands for massively-connected, high-throughput, and energy-efficient communications, several promising technologies have emerged and been discussed in 5G communication standards, including massive multiple-input multiple-output (MIMO)[1], millimeter-wave communications[2], and ultra-dense networks (UDNs)[3]. Among them, massive MIMO and UDN both aim at increasing the number of antennas or the deployment of small base stations (BSs) in a cell-centric way to achieve high capacity. However, the performance of multi-cell MIMO architecture suffers from inter-cell interference with the concept of cell boundaries[4]. To address this problem, a new architecture named the cell-free network has been proposed in a user-centric paradigm, where all access points (APs) in the network coordinate with each other to serve all users in the network simultaneously[5 – 6]. By deploying a mass of low-cost APs across the network and through effective cooperation among APs, cell-free networks achieve high-capacity coverage and diversity enhancement. However, when it comes to further capacity improvement, both hardware and power consumption require high costs, which cannot be ignored for next-generation communications.

Fortunately, reconfigurable intelligent surface (RIS) emerges as a key candidate technology for future 6G wireless systems[7 – 8]. Different from the traditional ways of antennas or BS densification, RIS, which comprises numerous low-cost passive reflecting elements, provides an energy-efficient alternative to improve the system spectrum efficiency by adjusting the phase shifts of its elements smartly, while being free from radio frequency chains and amplifiers. With the ability to manipulate the incident electromagnetic signals, RIS can be used to improve the channel rank[9], extend the coverage area[10], enhance the desired signals at the users, and constructively mitigate the undesired signals at unintended users. By introducing RIS into the cell-free network, higher spectrum and energy efficiency can be achieved with less power consumption[11 – 12].

Several research works have been devoted to jointly optimizing the transmit beamforming at the AP and the phase shifts at the RIS to guarantee the performance gain, including single-cell[13 – 14] and multi-cell[10] scenes. Additionally, in Ref. [15], the authors first added an ariel RIS to a cell-free system and proposed an iterative optimization algorithm to maximize the achievable rate of the user by the power allocation and the beamforming vector. In Ref. [16], the channel estimate scheme was investigated for RIS-assisted cell-free systems under spatially correlated channels. While the above works only considered the system with a single RIS, authors in Ref. [11] studied the sum-rate optimizing problem with multiple RISs in a centralized beamforming scheme. However, with the increase of the network scale, it is very intractable to collect all the instantaneous channel state information (CSI) and compute the high-dimensional information. Later, in Ref. [17], a fully decentralized design framework was proposed to incrementally and locally update the beamformers. However, in the presence of RISs, multiple iterations are required to reach a consensus for the phase shift design due to the coupling effect of the active beamformer and phase shift design. Despite reducing the complexity, it increases signaling exchange among APs and the processor cost for APs, introducing more potential delay and errors for CSI.

Inspired by Ref. [18], we propose a distributed framework for cooperative beamforming and phase shift design in RISs-aided cell-free systems. In order to avoid the drawbacks of centralized high-dimensional CSI exchange and high CPU processing complexity, as well as the issues of frequent CSI exchange and latency time among fully distributed APs, we leverage the centralized processing capability of the CPU to optimize the high-dimensional phase shifts brought by multiple RISs to improve system capacity, while each AP only locally optimizes the small-scale active beamforming. The main contributions of this work are summarized as follows. 1) A cooperative distributed beamforming design framework is proposed for the multi-RIS aided cell-free system, showing lower complexity and comparable spectrum efficiency to the centralized framework in Ref. [11]. 2) A weighted sum-rate (WSR) maximization problem for the cooperative distributed scheme is formulated, subject to transmit power constraints at APs and unit-modulus constraints of RIS. By employing the alternating optimization framework to decompose the non-convex problem, we innovatively derive a closed-form distributed solution to active beamforming, while the effective Riemannian conjugate gradient (RCG) algorithm is adopted to deal with the phase shifts of multiple RISs under unit-modulus constraints, and the discrete phase-shift case is additionally discussed. 3) Simulation results demonstrate the superior performance of the multi-RIS aided cell-free system compared with the traditional cellular network and the conventional cell-free system, and verify the effectiveness of the proposed low-complexity design.

The rest of this paper is organized as follows. Section 2 presents the system model and the formulation of the discussed problem. Section 3 introduces the proposed cooperative distributed beamforming design. Section 4 provides the numerical results to discuss the performance of the proposed design. Finally, we conclude this paper in Section 5.

## 2 System Model and Problem Formulation

In this paper, we consider a downlink RISs-aided cell-free system, where multiple distributed APs (each equipped with $M_t$ transmit antennas) cooperatively serve $K$ users (each equipped with $M_r$ receive antennas) with the aid of multiple RISs. All RISs are controlled by the CPU through wired or wireless control, while all APs are connected to the CPU by the backhaul link. The CPU is deployed for joint planning and control, which coordinates APs and RISs. We denote the index sets of APs, RISs, users and RIS reflecting elements as $\mathcal{B} = \{1,\cdots,B\}$, $\mathcal{L} = \{1,\cdots,L\}$, $\mathcal{K} = \{1,\cdots,K\}$ and $\mathcal{N} = \{1,\cdots,N\}$, respectively.

### 2.1 Transmitters

In the proposed cell-free network, all APs cooperate to serve all users by coherent transmission. Let $s_k, \forall k \in \mathcal{K}$ denote the transmitted symbol for the $k$-th user, satisfying $\mathbb{E}\left\{\left|s_k\right|^2\right\} = 1$. Then, the transmitted signal at the $b$-th AP is given as

$$\boldsymbol{x}_b = \sum_{k=1}^{K} \boldsymbol{w}_{b,k} s_k, \forall b \in \mathcal{B}, \tag{1}$$

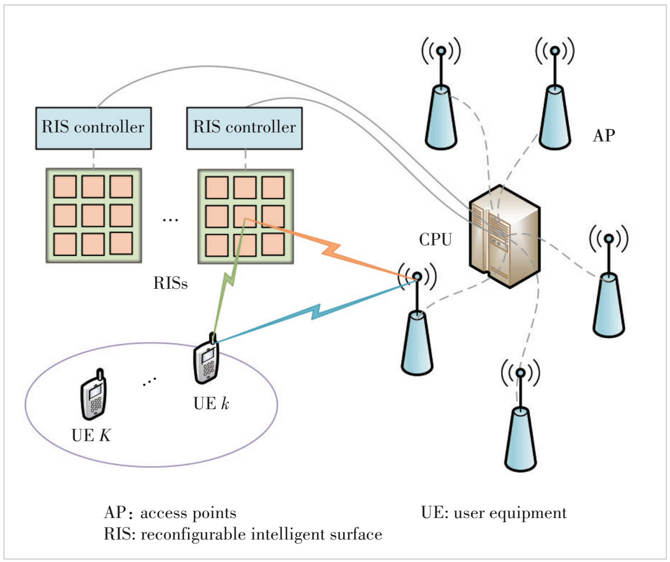
where $\boldsymbol{w}_{b,k} \in \mathbb{C}^{M_t \times 1}$ denotes the corresponding active beamforming vector designed for the $k$-th user at the $b$-th AP. The beamforming vectors satisfy the transmit power constraint $\sum_{k=1}^{K} \left\| \boldsymbol{w}_{b,k} \right\|^2 \leqslant P_{b,\max}$, where $P_{b,\max}$ denotes the power budget of the AP $b$.

### 2.2 Channel Model

Let $\boldsymbol{H}_{b,k}^H \in \mathbb{C}^{M_r \times M_t}$, $\boldsymbol{H}_{r,l,k}^H \in \mathbb{C}^{M_r \times N}$ and $\boldsymbol{G}_{b,l} \in \mathbb{C}^{N \times M_t}$ denote the complex equivalent baseband channel matrix between the $b$-th AP and the $k$-th user, between the $l$-th RIS and the $k$-th user, and between the $b$-th AP and the $l$-th RIS, respectively, $\forall b \in \mathcal{B}$, $\forall k \in \mathcal{K}$, and $\forall l \in \mathcal{L}$. We assume that the CSI of all the links can be perfectly known at the AP via the channel acquisition method[19]. Denote the phase shift of the $n$-th reflection element of the $l$-th RIS by $\theta_n^l \in [0, 2\pi]$. Then, by defining $\boldsymbol{\Phi}_l \triangleq \operatorname{diag}\left\{\phi_{l,1},\cdots,\phi_{l,N}\right\}, \forall l \in \mathcal{L}$, where $\phi_{l,n} = e^{j\theta_n^l}$, the received signal at the $k$-th UE can be expressed and simplified as:

$$\begin{aligned}\boldsymbol{y}_k = &\sum_{b=1}^{B}\sum_{m=1}^{K}\left(\boldsymbol{H}_{b,k}^H + \sum_{l=1}^{L}\boldsymbol{H}_{r,l,k}^H\boldsymbol{\Phi}_l\boldsymbol{G}_{b,l}\right)\boldsymbol{w}_{b,m}s_m + \boldsymbol{n}_k \overset{(a)}{=} \\ &\sum_{b=1}^{B}\sum_{m=1}^{K}\left(\boldsymbol{H}_{b,k}^H + \boldsymbol{H}_{r,k}^H\boldsymbol{\Phi}\,\boldsymbol{G}_b\right)\boldsymbol{w}_{b,m}s_m + \boldsymbol{n}_k \overset{(b)}{=} \\ &\sum_{b=1}^{B}\sum_{m=1}^{K}\bar{\boldsymbol{H}}_{b,k}^H\boldsymbol{w}_{b,m}s_m + \boldsymbol{n}_k,\end{aligned} \tag{2}$$

where $(a)$ holds by defining $\boldsymbol{\Phi} = \operatorname{diag}\left(\boldsymbol{\Phi}_1,\cdots,\boldsymbol{\Phi}_L\right)$, $\boldsymbol{H}_{r,k} = \left[\boldsymbol{H}_{r,1,k}^T,\cdots,\boldsymbol{H}_{r,L,k}^T\right]^T$, and $\boldsymbol{G}_b = \left[\boldsymbol{G}_{b,l}^T,\cdots,\boldsymbol{G}_{b,L}^T\right]^T$, and $(b)$ holds by defining




▲Figure 1. Downlink transmission in the multi-RIS aided cell-free system

$$\bar{\boldsymbol{H}}_{b,k}^{H} = \boldsymbol{H}_{b,k}^{H} + \sum_{l=1}^{L} \boldsymbol{H}_{\mathrm{r},l,k}^{H} \boldsymbol{\Phi}_{l} \boldsymbol{G}_{b,l}, \tag{3}$$

and $\boldsymbol{n}_k \sim \mathcal{CN}\left(\boldsymbol{0}, \sigma^2 \boldsymbol{I}_{M_r}\right)$ denotes the noise at the $k$-th user following the Gaussian distribution. Then, the achievable data rate of user $k$ can be given by:

$$R_k = \log\det\left(\boldsymbol{I} + \left(\sum_{b=1}^{B} \bar{\boldsymbol{H}}_{b,k}^{H} \boldsymbol{w}_{b,k}\right)\left(\sum_{b=1}^{B} \boldsymbol{w}_{b,k}^{H} \bar{\boldsymbol{H}}_{b,k}\right)\boldsymbol{Q}_k^{-1}\right), \tag{4}$$

where $\boldsymbol{Q}_k = \sum_{m=1, m\neq k}^{K} \left(\sum_{b=1}^{B} \bar{\boldsymbol{H}}_{b,k}^{H} \boldsymbol{w}_{b,m}\right)\left(\sum_{b=1}^{B} \boldsymbol{w}_{b,m}^{H} \bar{\boldsymbol{H}}_{b,k}\right) + \sigma^2 \boldsymbol{I}_{M_r}$.

### 2.3 Problem Formulation

In this paper, we aim at maximizing the WSR of the RISs-aided cell-free system by jointly optimizing the AP transmit beamforming $\boldsymbol{W}$ and phase shift matrix $\boldsymbol{\Phi}$, with the WSR written as

$$R_{\mathrm{sum}} = \sum_{k=1}^{K} \omega_k R_k, \tag{5}$$

where $\omega_k \in \mathbb{R}^{+}$ is a weighting factor representing the priority for user $k$.

Then, subject to the AP transmit power constraint and the unit-modulus constraints of RIS elements, the optimization problem can be expressed as

$$\begin{aligned} &\max_{\boldsymbol{W}, \boldsymbol{\Phi}} \ R_{\mathrm{sum}} \\ &\text{s.t.} \ \sum_{k=1}^{K} \left\| \boldsymbol{w}_{b,k} \right\|^2 \leqslant P_{b,\max}, \forall b \in \mathcal{B}, \\ &\quad \theta_n^l \in \mathcal{F}, \forall l \in \mathcal{L}, \forall n \in \mathcal{N}, \end{aligned} \tag{6}$$

where $\boldsymbol{W} \triangleq \left[\boldsymbol{w}_1, \cdots, \boldsymbol{w}_K\right] \in \mathbb{C}^{BM_t \times K}$, and $\boldsymbol{w}_k = \left[\boldsymbol{w}_{1,k}^T, \cdots, \boldsymbol{w}_{B,k}^T\right]^T$. Here, we assume $\mathcal{F} \triangleq \left\{\theta_n^l \,\middle|\, \left|e^{j\theta_n^l}\right| = 1\right\}, \forall l \in \mathcal{L}, \forall n \in \mathcal{N}$, and we will also discuss the design under the discrete phase shift constraints as follows. Apparently, due to the non-convex complex objective function and the unit-modulus constraint in Problem (6), the optimization of the phase shift matrix $\boldsymbol{\Phi}$ and the active beamforming matrix $\boldsymbol{W}$ is very challenging.

## 3 Proposed Cooperative Distributed Beamforming Design

To avoid the centralized overwhelming computation, we propose a cooperative distributed beamforming design for solving Problem (6), since the constraints are distributed. Meanwhile, due to the large dimension of variables and the coupling effect of active beamformer and phase shift design, the full distributed framework will lead to extensive CSI exchange among APs and even more to reach a consensus on the phase shift design. Therefore, in the proposed design, we take full advantage of the centralized processing of the CPU to optimize the high-dimensional $\boldsymbol{\Phi}$, while the active beamformers are computed locally by each AP, in a cooperative distributed way.

In the following, the alternating optimization approach is adopted to address the joint optimization problem, which is decomposed into the active beamforming and the phase optimization subproblems.

### 3.1 Reformulation of the Original Problem

By exploiting the equivalence of the sum-rate maximization problem and the weighted mean-square error (MSE) minimization problem[20], the original non-convex problem can be reformulated into a more tractable form. First, considering a linear receiver filter $\boldsymbol{u}_k \in \mathbb{C}^{M_r \times 1}$, the estimated signal vector of each user is given by $\hat{\boldsymbol{s}}_k = \boldsymbol{u}_k^H \boldsymbol{y}_k, \forall k \in \mathcal{K}$. Then, under the independence assumption of the signal and the noise, the MSE matrix can be written as

$$\begin{aligned} &\mathrm{mse}_k \triangleq \mathbb{E}_{\mathbf{s},\mathbf{n}}\left[\left(\hat{\boldsymbol{s}}_k - \boldsymbol{s}_k\right)\left(\hat{\boldsymbol{s}}_k - \boldsymbol{s}_k\right)^H\right] = \\ &\left(\boldsymbol{u}_k^H \sum_{b=1}^{B} \bar{\boldsymbol{H}}_{b,k}^H \boldsymbol{w}_{b,k} - 1\right)\left(\boldsymbol{u}_k^H \sum_{b=1}^{B} \bar{\boldsymbol{H}}_{b,k}^H \boldsymbol{w}_{b,k} - 1\right)^H + \\ &\boldsymbol{u}_k^H\left(\sum_{m=1, m\neq k}^{K} \left(\sum_{b=1}^{B} \bar{\boldsymbol{H}}_{b,k}^H \boldsymbol{w}_{b,m}\right)\left(\sum_{b=1}^{B} \boldsymbol{w}_{b,m}^H \bar{\boldsymbol{H}}_{b,k}\right) + \sigma_k^2 \boldsymbol{I}_{M_r}\right)\boldsymbol{u}_k, \forall k \in \mathcal{K} \end{aligned} \tag{7}$$

By introducing a set of auxiliary matrices $\boldsymbol{f} = \left\{f_k, \forall k\right\}$, Problem (6) can be reformulated as follows[20]:

$$\begin{aligned} &\max_{\boldsymbol{W}, \boldsymbol{u}, \boldsymbol{f}, \boldsymbol{\Phi}} \sum_{k=1}^{K} \omega_k\left(\log\left(f_k\right) - f_k \mathrm{mse}_k + 1\right), \\ &\text{s.t.} \ \sum_{k=1}^{K} \left\| \boldsymbol{w}_{b,k} \right\|^2 \leqslant P_{b,\max}, \forall b \in \mathcal{B}, \\ &\quad \theta_n^l \in \mathcal{F}, \forall l \in \mathcal{L}, \forall n \in \mathcal{N}. \end{aligned} \tag{8}$$

### 3.2 Optimizing Active Beamforming

Fixing all of the auxiliary matrices $\boldsymbol{u},\boldsymbol{f}$ and the phase shift matrix of RISs $\boldsymbol{\Phi}$, we can rewrite the active beamforming optimization problem as:

$$\begin{aligned}&\min_{\boldsymbol{W}} \sum_{k=1}^{K} \omega_k f_k \mathrm{mse}_k\\ &\text{s.t.} \sum_{k=1}^{K} \left\| \boldsymbol{w}_{b,k} \right\|^2 \leqslant P_{b,\max}, \forall b \in \mathcal{B}.\end{aligned} \tag{9}$$

By substituting $\mathrm{mse}_k$ in Eq. (7) into the objective function in Problem (9) and ignoring the unrelated constant terms, we simplify the above optimization problem as

$$\begin{aligned}&\min_{\boldsymbol{W}} \mathrm{Tr}\left(\boldsymbol{W}^H \boldsymbol{V} \boldsymbol{W}\right) - 2\Re\left\{\mathrm{Tr}\left(\boldsymbol{Q}^H \boldsymbol{W}\right)\right\}\\ &\text{s.t.} \sum_{k=1}^{K} \left\| \boldsymbol{w}_{b,k} \right\|^2 \leqslant P_{b,\max}, \forall b \in \mathcal{B},\end{aligned} \tag{10}$$

where

$$\boldsymbol{V} \triangleq \begin{pmatrix} \boldsymbol{V}_{1,1} & \cdots & \boldsymbol{V}_{1,B} \\ \vdots & \ddots & \vdots \\ \boldsymbol{V}_{B,1} & \cdots & \boldsymbol{V}_{B,B} \end{pmatrix}, \tag{11}$$

$$\boldsymbol{V}_{bb'} \triangleq \sum\nolimits_{k=1}^{K} \omega_k f_k \bar{\boldsymbol{H}}_{b,k} \boldsymbol{u}_k \boldsymbol{u}_k^H \bar{\boldsymbol{H}}_{b',k}^H, \tag{12}$$

$$\boldsymbol{Q} \triangleq \left[\boldsymbol{q}_1, \cdots, \boldsymbol{q}_K\right], \tag{13}$$

$$\boldsymbol{q}_k \triangleq \left[\boldsymbol{q}_{1,k}^T, \boldsymbol{q}_{2,k}^T, \cdots, \boldsymbol{q}_{B,k}^T\right]^T, \tag{14}$$

$$\boldsymbol{q}_{b,k} \triangleq \omega_k f_k \bar{\boldsymbol{H}}_{b,k} \boldsymbol{u}_k, \tag{15}$$

and $\Re\{\cdot\}$ denotes the real part of its argument. We can observe that Problem (10) is a standard quadratically constrained quadratic program (QCQP) problem, which can be optimally solved by many existing methods such as the alternating direction method of multipliers (ADMM) and the standard convex tools[11]. However, these centralized methods contribute to high computational complexity. Here, with the power budget constraint, we provide a closed-form distributed solution by introducing the Lagrange multipliers method. According to the first-order optimal condition for each AP $b$ and each user $k$, we can obtain

$$\boldsymbol{w}_{b,k}^{\mathrm{opt}} = \left(\boldsymbol{V}_{bb} + \lambda_b \boldsymbol{I}_{M_t}\right)^{-1} \left(\boldsymbol{q}_{b,k} - \boldsymbol{\xi}_{b,k}\right), \tag{16}$$

where $\lambda_b$ is the introduced Lagrange multiplier updated via the bisection method. $\boldsymbol{\xi}_{b,k} \triangleq \sum\nolimits_{b' \in \mathcal{B} \setminus \{b\}} \boldsymbol{V}_{bb'} \boldsymbol{w}_{b',k}$, which implies the information about the channel between AP $b$ and the other APs, and about the beamforming designs adopted by the other APs for user $k$. Moreover, in the distributed design, each AP locally computes its beamformer $\boldsymbol{w}_{b,k}$ in parallel with the other APs. So based on the fixed $\boldsymbol{\xi}_{b,k}$, each AP updates its beamformer vector at iteration $t$ as

$$\boldsymbol{w}_{b,k}^{(t)} = (1 - \alpha)\boldsymbol{w}_{b,k}^{(t-1)} + \alpha \boldsymbol{w}_{b,k}^{\mathrm{opt}}, \tag{17}$$

where $\alpha \in \left(0,1\right]$. The update in Eq. (17) is to limit the variation of the precoding vectors between consecutive iterations, where the step size $\alpha$ needs to be chosen properly to strike a balance between convergence speed and accuracy.

### 3.3 Optimizing Auxiliary Variables

For given active beamforming matrices $\left\{\boldsymbol{w}_{b,k}, \forall b, \forall k\right\}$ and $\boldsymbol{\Phi}$, the optimization problem can be expressed as

$$\max_{\boldsymbol{u},\boldsymbol{f}} \sum_{k=1}^{K} \omega_k \left(\log\left(f_k\right) - f_k \mathrm{mse}_k\right). \tag{18}$$

By substituting Eq. (7) into the objective function in Problem (18), it can be easily seen that the form is concave with respect to $\boldsymbol{u}_k$ and to $f_k$. Thus, the optimal solution of them can be easily obtained by checking the first order optimality condition as follows:

$$\boldsymbol{u}_k^{\mathrm{opt}} = \left(\sum_{m=1}^{K} \left(\sum_{b=1}^{B} \bar{\boldsymbol{H}}_{b,k}^H \boldsymbol{w}_{b,m}\right)\left(\sum_{b=1}^{B} \boldsymbol{w}_{b,m}^H \bar{\boldsymbol{H}}_{b,k}\right) + \sigma_k^2 \boldsymbol{I}_{M_r}\right)^{-1} \sum_{b=1}^{B} \bar{\boldsymbol{H}}_{b,k}^H \boldsymbol{w}_{b,k}, \tag{19}$$

$$f_k^{\mathrm{opt}} = \mathrm{mse}_k^{-1}, \tag{20}$$

where

$$\mathrm{mse}_k = 1 - \sum_{b}^{B} \boldsymbol{w}_{b,k}^H \bar{\boldsymbol{H}}_{b,k} \boldsymbol{u}_k. \tag{21}$$

### 3.4 Optimizing Phase Shifts

Next, we focus our attention on optimizing the phase shifts $\boldsymbol{\Phi}$, based on the optimized $\boldsymbol{u},\boldsymbol{f}$ and $\left\{\boldsymbol{w}_{b,k}, \forall b, \forall k\right\}$. By ignoring the unrelated terms, the phase shifts optimization problem is presented as

$$\begin{aligned}&\min_{\boldsymbol{\Phi}} \sum_{k=1}^{K} \omega_k f_k \mathrm{mse}_k\\ &\text{s.t. } \theta_n^l \in \mathcal{F}, \forall l \in \mathcal{L}, \forall n \in \mathcal{N}.\end{aligned} \tag{22}$$

This problem is non-convex due to the unit-modulus constraint. Substituting Eq. (3) into Eq. (7) and following some further manipulations, the objective function is represented as

$$\sum_{k=1}^{K}\omega_k f_k\Bigg[\sum_{i=1}^{L}\sum_{j=1}^{L}\mathrm{Tr}\left(\boldsymbol{\Phi}_i^H\boldsymbol{A}_{i,j,k}\boldsymbol{\Phi}_j\boldsymbol{B}_{i,j}\right)+ \sum_{l=1}^{L}\mathrm{Tr}\left(\boldsymbol{\Phi}_l^H\left(\boldsymbol{C}_{l,k}-\boldsymbol{D}_{l,k}\right)\right)+\sum_{l=1}^{L}\mathrm{Tr}\left(\boldsymbol{\Phi}_l\left(\boldsymbol{C}_{l,k}-\boldsymbol{D}_{l,k}\right)^H\right)\Bigg], \tag{23}$$

with the notations as follows:

$$\boldsymbol{A}_{i,j,k}=\boldsymbol{H}_{\mathrm{r},i,k}\boldsymbol{u}_k\boldsymbol{u}_k^H\boldsymbol{H}_{\mathrm{r},j,k}^H, \tag{24}$$

$$\boldsymbol{B}_{i,j}=\sum_{m=1}^{K}\left(\sum_{b=1}^{B}\boldsymbol{G}_{b,j}\boldsymbol{w}_{b,m}\right)\left(\sum_{b=1}^{B}\boldsymbol{w}_{b,m}^H\boldsymbol{G}_{b,i}^H\right), \tag{25}$$

$$\boldsymbol{C}_{l,k}=\boldsymbol{H}_{\mathrm{r},l,k}\boldsymbol{u}_k\boldsymbol{u}_k^H\sum_{m=1}^{K}\left(\sum_{b=1}^{B}\boldsymbol{H}_{b,k}^H\boldsymbol{w}_{b,m}\right)\left(\sum_{b=1}^{B}\boldsymbol{w}_{b,m}^H\boldsymbol{G}_{b,l}^H\right), \tag{26}$$

$$\boldsymbol{D}_{l,k}=\boldsymbol{H}_{\mathrm{r},l,k}\boldsymbol{u}_k\sum_{b=1}^{B}\boldsymbol{w}_{b,k}^H\boldsymbol{G}_{b,l}^H. \tag{27}$$

By defining vector $\boldsymbol{\phi}_l=\left[\phi_{l,1},\cdots,\phi_{l,n},\cdots,\phi_{l,N}\right]^T$, and $\boldsymbol{\phi}=\left[\boldsymbol{\phi}_1^T,\cdots,\boldsymbol{\phi}_L^T\right]^T$, we arrive at $\mathrm{Tr}\left(\boldsymbol{\Phi}_i^H\boldsymbol{A}_{i,j,k}\boldsymbol{\Phi}_j\boldsymbol{B}_{i,j}\right)=\boldsymbol{\phi}^H\left(\boldsymbol{A}_{i,j,k}\odot\boldsymbol{B}_{i,j}^T\right)\boldsymbol{\phi}$, where $\odot$ is a Hadamard product operator. For ease of representation, we let $\boldsymbol{Z}_{i,j}=\left(\sum_{k=1}^{K}\omega_k f_k\boldsymbol{A}_{i,j,k}\right)\odot\boldsymbol{B}_{i,j}^T$, $\hat{\boldsymbol{Z}}=\begin{pmatrix}\boldsymbol{Z}_{1,1} & \cdots & \boldsymbol{Z}_{1,L}\\ \vdots & \ddots & \vdots\\ \boldsymbol{Z}_{L,1} & \cdots & \boldsymbol{Z}_{L,L}\end{pmatrix}$, $\boldsymbol{p}_l=\left[\sum_{k=1}^{K}\omega_k f_k\left[\boldsymbol{C}_{l,k}-\boldsymbol{D}_{l,k}\right]_{1,1},\cdots,\sum_{k=1}^{K}\omega_k f_k\left[\boldsymbol{C}_{l,k}-\boldsymbol{D}_{l,k}\right]_{N,N}\right]^T$, and $\boldsymbol{p}=\left[\boldsymbol{p}_1^T,\cdots,\boldsymbol{p}_L^T\right]^T$. Hence, the optimization of Problem (22) for phase shifts $\boldsymbol{\phi}$ can be reformulated as:

$$\begin{aligned}&\min_{\boldsymbol{\phi}}\ \boldsymbol{\phi}^H\hat{\boldsymbol{Z}}\boldsymbol{\phi}+2\Re\mathrm{e}\left\{\boldsymbol{p}^H\boldsymbol{\phi}\right\}\\ &\text{s.t. } \theta_n^l\in\mathcal{F},\forall l\in\mathcal{L},\forall n\in\mathcal{N}.\end{aligned} \tag{28}$$

We have $\mathcal{F}\triangleq\left\{\theta_n^l\middle|\ \left|e^{j\theta_n^l}\right|=1\right\}$ in the non-convex problem, and we notice that the unit modulus constraints form a complex circle manifold in fact, as

$$\mathcal{M}^{NL}=\left\{\phi\in\mathbb{C}^{NL}:\left|\phi_{1,1}\right|=\ldots=\left|\phi_{L,N}\right|=1\right\}. \tag{29}$$

The formed search space is the product of $NL$ circles in the complex plane, which is a Riemanifold of $\mathbb{C}^{NL}$ with the product geometry. Thereby, we propose the Riemannian conjugate gradient method for the phase shifts optimization. Specifically, Problem (28) can be alternately solved by carrying out the following steps at each iteration $r$: 1) Firstly, compute the gradient in Euclidean space $\nabla f\left(\boldsymbol{\phi}_r\right)=2\hat{\boldsymbol{Z}}\boldsymbol{\phi}_r+2\boldsymbol{p}^*$; 2) Compute the Riemannian gradient $\mathrm{grad}\ f\left(\boldsymbol{\phi}_r\right)=\mathrm{Proj}_{\boldsymbol{\phi}_r}\nabla f\left(\boldsymbol{\phi}_r\right)=\nabla f\left(\boldsymbol{\phi}_r\right)-\Re\left\{\nabla f\left(\boldsymbol{\phi}_r\right)\odot\boldsymbol{\phi}_r^*\right\}\odot\boldsymbol{\phi}_r$; 3) Then, update the search direction for the RCG method on manifold $\boldsymbol{\eta}_{r+1}=-\mathrm{grad}f\left(\boldsymbol{\phi}_{r+1}\right)+\beta_r\mathcal{T}_{\boldsymbol{\phi}_r\to\boldsymbol{\phi}_{r+1}}\left(\boldsymbol{\eta}_r\right)$, where $\mathcal{T}_{\boldsymbol{\phi}_r\to\boldsymbol{\phi}_{r+1}}\left(\boldsymbol{\eta}_t\right)\triangleq T_{\boldsymbol{\phi}_r}\mathcal{M}^{NL}\mapsto T_{\boldsymbol{\phi}_{r+1}}\mathcal{M}^{NL}$: $\boldsymbol{\eta}_r\mapsto\boldsymbol{\eta}_r-\Re\mathrm{e}\left\{\boldsymbol{\eta}_r\odot\boldsymbol{\phi}_{r+1}^*\right\}\odot\boldsymbol{\phi}_{r+1}$ and $\beta_r$ is chosen as the Polak-Ribiere parameter; 4) Finally, map the solution into the manifold $\mathcal{M}^{NL}$ as $\boldsymbol{\phi}_{r+1}=\mathcal{R}_{\boldsymbol{\phi}_r}\left(\alpha_r\boldsymbol{\eta}_r\right)$ with step size $\alpha_r$ by retraction operator $\mathcal{R}_{\boldsymbol{\phi}_r}\left(\alpha_r\boldsymbol{\eta}_r\right)\triangleq T_{\boldsymbol{\phi}_r}\mathcal{M}^{NL}\mapsto\mathcal{M}^{NL}$: $\alpha_r\boldsymbol{\eta}_r\mapsto\mathrm{vec}\left[\dfrac{\boldsymbol{\phi}_r+\alpha_r\boldsymbol{\eta}_r}{\left|\boldsymbol{\phi}_r+\alpha_r\boldsymbol{\eta}_r\right|}\right]$.

### 3.5 Complexity Analysis and Algorithm Supplements

Based on the solutions to the above sub-problems, we implement the proposed cooperative distributed beamforming design by iteratively updating the variable set $\left\{\boldsymbol{w},\boldsymbol{u},\boldsymbol{f},\boldsymbol{\xi},\boldsymbol{\phi}\right\}$. At each iteration, $\boldsymbol{w}$ is optimized locally at each AP, while CPU optimizes $\boldsymbol{u},\boldsymbol{f},\boldsymbol{\phi}$ and computes $\boldsymbol{\xi}$ in a centralized mode, which is guaranteed to converge at least a locally optimal solution[18]. Note that APs need to share the estimated CSI $\left\{\boldsymbol{H}_{b,k},\forall k\right\}$, $\left\{\boldsymbol{H}_{\mathrm{r},l,k},\forall k,l\right\}$, and $\left\{\boldsymbol{G}_{b,l},\forall l\right\}$ with CPU, so the required backhaul signaling for CSI exchange is $BM_t\left(KM_r+NL\right)+NLKM_r$. Moreover, according to Section 3.2, each AP needs to receive $\left\{\boldsymbol{u},\boldsymbol{f},\boldsymbol{\xi},\boldsymbol{\phi}\right\}$ from CPU (or initialize them) at each iteration, which requires $KM_r+K+NL+BM_tK$ backhaul signaling, and then APs need to feed back $\left\{\boldsymbol{w}_{b,k},\forall k\right\}$ to CPU, which requires $BM_tK$ backhaul signaling. Therefore, the total required signaling overhead of the proposed design is $BM_t\left(KM_r+NL\right)+NLKM_r+I\left(KM_r+K+NL+2BM_tK\right)$, where $I$ denotes the number of iterations. It reduces the signaling overhead compared with the fully distributed framework, which leads to $B^2\left(M_t\left(KM_r+NL\right)+NLKM_r+I\left(KM_r+K+NL+M_tK\right)\right)$ signaling overhead, in the case of large $B$ in the cell-free network.

In the meantime, the main complexity is dominated by the matrix inverse, which involves complexity $\mathcal{O}\left(BKM_t^3\right)$, and by the gradient computation in the RCG method, which involves $\mathcal{O}\left(K^2N^2L^2\right)$. Compared with the design using semidefinite relaxation (SDR) or convex optimization toolbox, which leads to the complexity $\mathcal{O}\left(N^{3.5}L^{3.5}\right)$, the proposed approach realized great computational complexity reduction.

As a supplement, when the discrete phase shifts are considered, we adopt the common solution and approximation projection[21], to address the non-convex constraint. The core idea of this method is first to obtain a continuous solution $\theta_n^{l\ \mathrm{opt}},\forall l,\forall n$ that satisfies the unit modulus constraint, and then simply project the solution to the nearest discrete value in the set

$\hat{\mathcal{F}} \triangleq \left\{ \theta_n^l \middle| \ \theta_n^l = e^{j\frac{2\pi(x-1)}{\Delta}}, x = 1,\cdots,\Delta \right\}$, where $\Delta = 2^{\hat{b}}$ and $\hat{b}$ is the number of discrete bits. It can be written as follows:

$$\theta_n^{l\star} = \arg\min_{\varphi \in \hat{\mathcal{F}}} \left| \theta_n^{l\,\mathrm{opt}} - \varphi \right|, \forall l \in \mathcal{L}, \forall n \in \mathcal{N}. \tag{30}$$

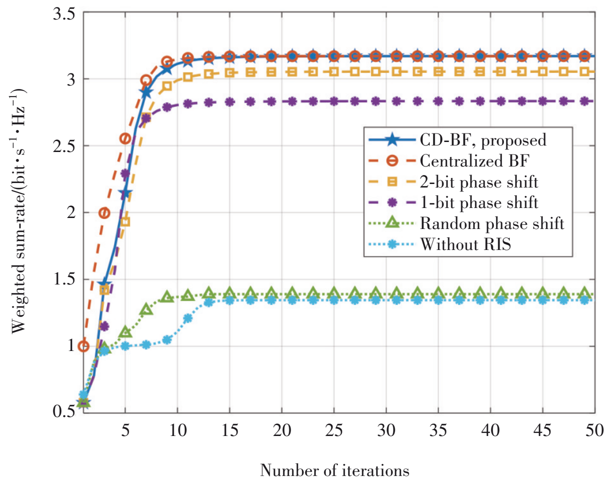
## 4 Simulation Results

In this section, simulation results are presented to demonstrate the performance of the proposed cooperative distributed beamforming design in the multi-RIS aided cell-free system. The numbers of APs, users and RISs are $B = 3$, $K = 3$, and $L = 3$, and each AP and user is equipped with $M_t = M_r = 2$ antennas. Considering a 3D scenario, three APs are located at $(0, 100\text{ m}, 3\text{ m})$, $(-50\sqrt{3}\text{ m}, -50\text{ m}, 3\text{ m})$, and $(50\sqrt{3}\text{ m}, -50\text{ m}, 3\text{ m})$, respectively, and users are randomly distributed in a circle centered at $(0, 0)$ with a radius of 5 m. The height of the users is set as 1.5 m. In particular, three RISs are deployed near users right above the points $(0, 20\text{ m})$, $(-15\text{ m}, -15\text{ m})$, and $(15\text{ m}, -15\text{ m})$, respectively, facing the ground with an altitude of 6 m, so that all of them can cooperate with all APs to serve the users.

For the large-scale fading, we use the urban macro (UMa) path loss model in 3GPP specification TR 38.901[22] as the distance-dependent channel path loss model, with a carrier frequency set as 5.8 GHz. Specifically, the path loss model for $\boldsymbol{G}_{b,l}$ and $\boldsymbol{H}_{r,l,k}$ can be given by $\mathcal{L}_{\mathrm{LoS}} = 43.27 + 22.0\log(d)$, where $d$ represents the distance between the transmitter and the receiver. Meanwhile, due to the randomness of users and the long distance between the AP and users, LoS propagation may not necessarily be guaranteed for the AP-user channels, so the path loss for $\boldsymbol{H}_{b,k}$ is assumed as $\mathcal{L}_{\mathrm{NLoS}} = \max\left(\mathcal{L}_{\mathrm{LoS}}, \mathcal{L}'_{\mathrm{NLoS}}\right)$, where $\mathcal{L}'_{\mathrm{NLoS}} = 28.81 + 39.08\log(d)$. For the small-scale fading, we consider the Rician fading channel model. Let $\kappa_{\mathrm{AU}} = 0$, $\kappa_{\mathrm{RU}} = 3$, and $\kappa_{\mathrm{AR}} \rightarrow \infty$ denote the Rician factors of the AP-user, RIS-user, and AP-RIS channels, respectively. The transmit power budget is set as $P_{b,\max} = P_{\max} = 20\,\mathrm{dBm}, \forall b$, the noise power is set as $\sigma^2 = -80$ dBm, and the weight $\omega_k$ for each user is set as 1 equally.

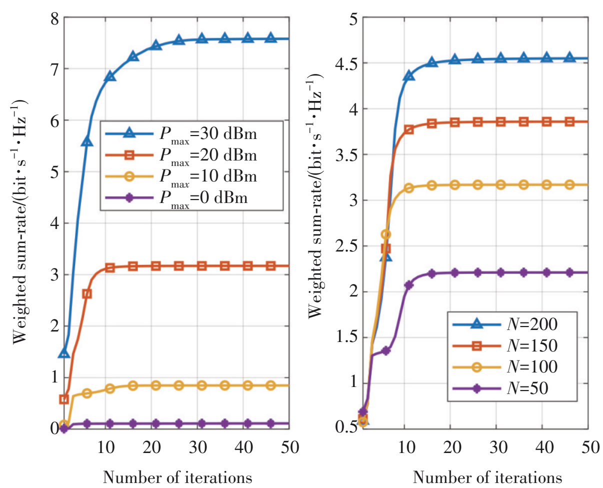
Fig. 2 illustrates the convergence behavior of all the proposed algorithms. It can be seen that, when $N = 100$ and the convergence error is not greater than 0.1%, the proposed cooperative distributed beamforming (CD-BF) algorithm converges within 15 iterations. Despite the distributed design of active beamforming in the proposed method, the convergence performance is almost the same as that of the centralized beamforming (BF)[11], without causing any performance loss. Besides, the cases of discrete bits, random phases, and without RIS converge within 15 iterations as well.

Fig. 3 presents the convergence behavior of the proposed design under different AP transmit power budgets $P_{\max}$ and varying numbers of elements $N$. Fig. 3(a) illustrates that as $P_{\max}$ increases, the convergence speed noticeably slows down, while the weighted sum-rate performance significantly improves. Similarly, in Fig. 3(b), it can be observed that as $N$ increases, the algorithm converges slightly slower but within 20 iterations. This depicts the good convergence performance of the proposed design.




CD-BF: cooperative distributed beamforming algorithm
RIS: reconfigurable intelligent surface

▲Figure 2. Convergence behavior when $N$=100



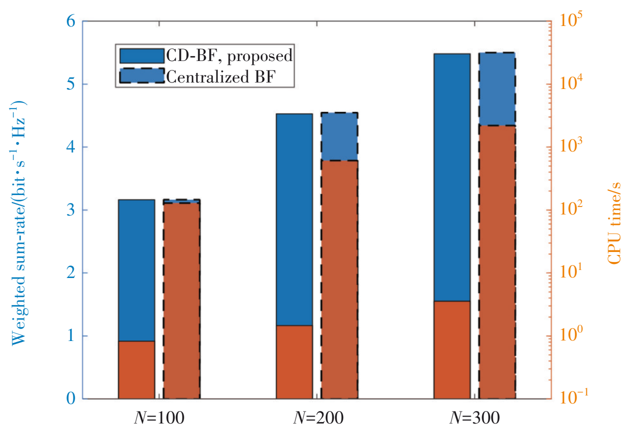

(a) $N$ = 100 (b) $P_{\max}$ = 20 dBm

▲Figure 3. Convergence behavior under different power budgets and numbers of elements $N$

Fig. 4 shows the performance comparison between the proposed and the centralized algorithm in terms of weighted sum-rate and CPU running time, with different numbers of reflecting elements $N$=100, 200, and 300. First, it is observed that both algorithms exhibit almost identical sum-rate performance under different $N$. However, due to the proposed cooperative distributed design, which avoids high-dimensional matrix calculations, and the fast optimization speed of the manifold method, the proposed one achieves better speed performance than the centralized algorithm. In addition, as $N$ increases, the runtime of the proposed algorithm remains in the same order of $10^0$, while the centralized algorithm's runtime increases from $10^2$ to $10^3$, highlighting the low complexity advantage of the proposed algorithm.

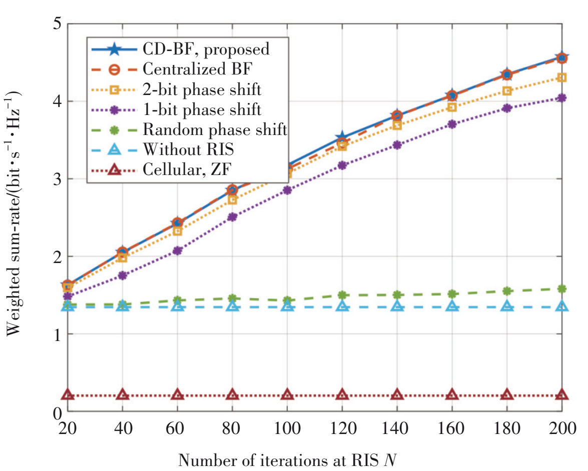
Fig. 5 compares the sum-rate performance with the size $N$ of RIS. The results indicate that the proposed design achieves higher performance gain as $N$ increases, comparable to centralized design. Additionally, with the rise of $N$, the approximation loss of low-bit discrete phases becomes larger, which implies the significance of the precise phase design when it comes to a large size of RIS, while balancing the overhead and complexity of channel estimation. Furthermore, we discuss a traditional cellular network baseline with multiple small cells serving the nearest user in the setting scene without RIS assistance, where classical zero-forcing (ZF) precoding is used for transmission. It can be observed that compared with this baseline and the traditional cell-free network without RIS, the RIS-assisted cell-free system architecture achieves significant spectral efficiency improvement.

In Fig. 6, we compare the WSR performance under two different deployment strategies, namely, the near-AP side and the near-user side. In the setting scenario, the results reveal that, considering edge users that are far from APs, the near-user deployment outperforms the near-AP one, regardless of continuous or discrete phase shifts. Moreover, it can be seen that, even compared with the traditional cell-free scenario with $B' = B + L$ APs, the proposed RIS-aided architecture still provides significant gains while being cost-effective and energy-efficient.




CD-BF: cooperative distributed beamforming algorithm

**▲ Figure 4. Weighted sum rate and CPU running time comparison between the proposed and the centralized BF**

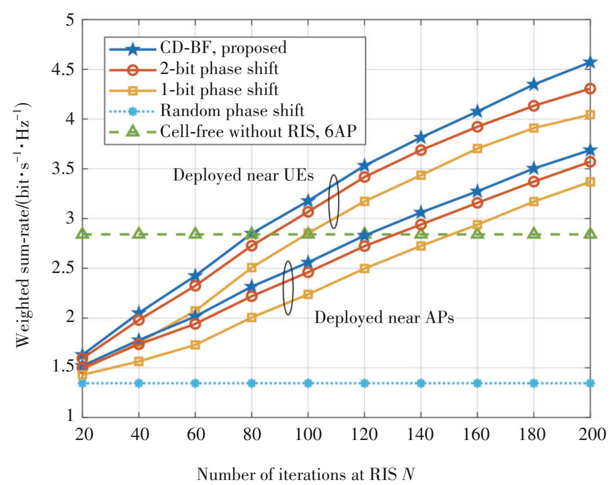



CD-BF: cooperative distributed beamforming algorithm
RIS: reconfigurable intelligent surfaces
ZF: zero-forcing

**▲ Figure 5. Weighted sum rate versus the number of reflecting elements $N$**

# 5 Conclusions

In this paper, we investigate joint active beamforming and phase shift design for the multi-RIS aided cell-free system. The weighted sum-rate maximization problem under the proposed cooperative distributed beamforming design framework has been considered, which is firstly converted to a tractable form by exploiting the relationship between the sum rate and the sum MSE. Further, we derive the distributed closed-form




AP: access point
CD-BF: cooperative distributed beamforming algorithm
RIS: reconfigurable intelligent surfaces
UE: user equipment

**▲ Figure 6. Weighted sum-rate versus $N$ with different RIS deployment strategies**

solution from the active beamforming and update the phase shifts using the RCG method. By iteratively optimizing the two objectives across APs and CPU, the proposed design converges to a stationary point, outperforming the centralized framework in terms of lower complexity and equivalent spectrum efficiency. In addition, our numerical results demonstrate the remarkable potential of RIS in improving the network capacity compared with conventional cellular and cell-free systems.

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