Transmit Beamforming for QoE Improvement in C-RAN with Mobile Virtual Network Operators

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***Abstract*—Network slicing enables mobile virtual network operators (MVNOs) to lease network resources from a mobile network operator (MNO). The cloud radio access network (C-RAN) architecture reduces the capital and operational expenditures for the MNO and also facilitates MVNOs running virtual machines on the cloud server. In this paper, we propose a beamforming scheme that coordinates multiple remote radio heads (RRHs) in C-RAN to improve the quality of experience (QoE) of users by maximizing their aggregate weighted quality of service (QoS). We model the QoS of each mobile user by a sigmoidal function and formulate the beamforming design as a non-convex optimization problem. By introducing an interference threshold, we first develop an iterative algorithm to determine a suboptimal solution of the original problem. Based on simulation results, we then show that a suitable interference threshold can be obtained in an off-line manner such that the suboptimal solution is a close-to-optimal solution of the original non-convex problem. Simulation results also show that the proposed scheme can significantly improve the aggregate weighted QoS of the mobile users compared to the traditional design where the weighted system sum rate is maximized.**

I. Introduction

With the proliferation of smart user equipments (UEs) (*e.g.*, smartphones, tablets), mobile applications such as online video gaming have significantly increased the demand for high data rate mobile service. Although various novel techniques, such as femtocell networks, multiple-input multiple-output (MIMO), and coordinated multi-point (CoMP) transmission, have been proposed, they either require a dense deployment of base stations or complex baseband signal processing techniques to increase the spectral efficiency.

In this regard, the cloud radio access network (C-RAN) is a promising network architecture for wireless cellular networks [1]. In C-RAN, the module used for baseband signal processing is detached from the radio transceiver module. The baseband signal processing module located at a cloud server is referred to as the *baseband unit* (BBU). The base station in C-RAN, which is only composed of radio signal transceivers, is referred to as the *remote radio head* (RRH). The RRH is connected to the BBU on a cloud server by optical fiber. Multiple BBUs form a BBU pool on the cloud server that can be shared by multiple RRHs. In C-RAN, the baseband signals are processed by the BBU pool on the cloud server which can coordinate multiple RRHs to perform beamforming. An energy-efficient beamforming design with target signal-to-interference-plus-noise ratio (SINR) for mobile users has been studied in [2]. Beamforming design in C-RAN with limited backhaul capacity was investigated in [3]. The works in [4] and [5] studied the beamforming design and RRHs clustering problem with capacity-limited backhaul in C-RAN.

By employing network function virtualization, the network resources owned by a mobile network operator (MNO) can be divided into *virtual base stations* [6] or *network slices* [7]. A virtual base station, which is allocated a frequency band and a fraction of the airtime of a real base station, can be leased to a mobile virtual network operator (MVNO) [6], [8]. MVNOs can control virtual base stations via virtual machines (VMs) to serve their customers. Although network function virtualization can be applied in the existing wireless cellular networks, it is more suitable for C-RAN, as VMs can be located on the cloud server of the BBU pool and control the RRHs in a centralized manner to utilize the leased network resources more efficiently.

Since MVNOs have limited network resources to serve mobile users with different mobile applications, it is important to improve the quality of experience (QoE) for these users. For MVNOs competing for the market share, QoE of mobile users may directly affect the utility of the network resources leased from MNOs. However, QoE evaluates the subjective acceptability of applications perceived by end users [9], so it is difficult to be used as a design criterion in the resource allocation for real-time applications. On the other hand, the quality of service (QoS), which evaluates the network performance in an objective manner, is closely related to the QoE [10], [11]. The QoS of a mobile user can be modeled by a sigmoidal function with its received SINR as the input parameter [12]. Since sigmoidal functions are non-convex, determining the optimal beamforming vectors is challenging.

Furthermore, the channel state information (CSI) plays a critical role for the beamforming design in C-RAN. This is because the downlink precoded signals may not be stored at RRHs, as the RRH in C-RAN contains radio signal transceiver module only. If the actual link quality from RRHs to a UE is worse than the estimated value, then the UE may not be able to decode the signal received from RRHs. In this case, the QoS received by mobile users will be severely degraded. In this paper, we consider the perfect CSI situation. We first formulate the beamforming design as a non-convex optimization problem. We then introduce an interference threshold, transform our problem, and solve it by a suboptimal iterative algorithm.

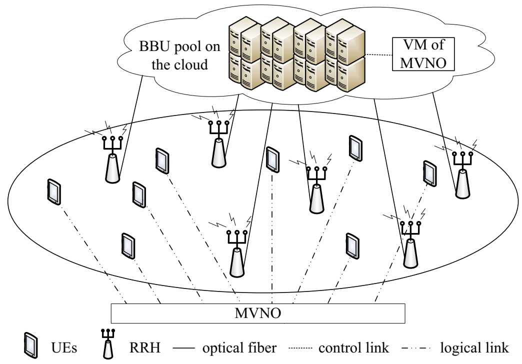

Fig. 1. The example of C-RAN where an MVNO leases RRHs and spectrum resources to serve the UEs of mobile users by running a VM on the cloud server hosting the BBU pool.

Simulation results show that the proposed algorithm achieves a close-to-optimal solution of the original problem and improves the aggregate weighted QoS for mobile users. Thus, the QoE of mobile users served by the MVNO can be enhanced.

The rest of this paper is organized as follows. In Section II, we introduce the considered system model. In Section III, we present the problem formulation and propose an iterative algorithm. Simulation results are provided in Section IV. Conclusions are given in Section V. In this paper, the following notations are adopted: $\mathbf{X}^{\mathsf{H}}$, $\mathsf{Tr}(\mathbf{X})$, and $\mathsf{Rank}(\mathbf{X})$ represent the conjugate transpose, trace, and rank of matrix $\mathbf{X}$, respectively; $\mathbb{C}$ is the set of complex numbers, $\mathbb{C}^{m\times n}$ represents the set of $m\times n$ complex matrices, $\mathbb{H}^n$ denotes the set of $n\times n$ Hermitian matrices; $|\cdot|$ is the absolute value, $\|\cdot\|$ represents the ℓ_2-norm, $\mathbb{E}[\cdot]$ denotes expectation; $\mathbf{x}\succeq\mathbf{0}$ means each element in vector $\mathbf{x}$ is non-negative, $\mathbf{X}\succeq\mathbf{0}$ means matrix $\mathbf{X}$ is positive semidefinite, $\mathsf{diag}(\mathbf{x})$ denotes a diagonal matrix with the elements of vector $\mathbf{x}$ on the main diagonal, $\mathbf{x}_{m:n}$ returns a vector with the m^{th} to the n^{th} elements in vector $\mathbf{x}$; $\mathbf{I}_n$ is the $n\times n$ identity matrix, $\mathbf{0}_n$ denotes the $n\times 1$ all-zero vector, $\otimes$ stands for the Kronecker product, and $\mathcal{CN}(0,\sigma^2)$ is the zero-mean complex Gaussian distribution with variance σ^2.

II. System Model

We consider the downlink data transmission in C-RAN architecture. The RRHs and the spectrum resources in the C-RAN are leased to MVNOs. An MVNO can operate a VM on the cloud server that is hosting the BBU pool to control the RRHs in C-RAN. The BBU pool on the cloud server communicates with the RRHs via optical fibers which are referred to as the backhaul. Let $\mathcal{M}=\{1,\dots,M\}$ denote the set of RRHs in C-RAN. Each RRH is equipped with $N\geq 1$ antennas. We assume that MVNOs can share RRHs in a time division manner. This can be achieved by letting the MNO allocate a fraction of the airtime of the RRHs to each MVNO [6]. Thus, an MVNO can exclusively use its leased spectrum resource to serve its customers. For simplicity, we consider a single MVNO in our system model. An example of the considered system is given in Fig. 1.

We consider that each mobile user has a UE. We use "mobile user" and "UE" interchangeably. Let $\mathcal{K}=\{1,\dots,K\}$ denote the set of UEs served by an MVNO. We assume that each UE in set $\mathcal{K}$ is equipped with a single antenna for low receiver complexity. As beamforming and CoMP are employed, a UE can be associated with multiple RRHs in set $\mathcal{M}$ simultaneously. The processed signal transmitted from RRH $m\in\mathcal{M}$ to UE $k\in\mathcal{K}$ is given by

$$\mathbf{w}_{m,k}s_k, \tag{1}$$

where $\mathbf{w}_{m,k}\in\mathbb{C}^{N\times 1}$ is the beamforming vector for user k on RRH m, and $s_k\in\mathbb{C}$ denotes the data symbol for user k. Without loss of generality, we assume that $\mathbb{E}\left[|s_k|^2\right]=1$, $\forall\, k\in\mathcal{K}$. The signal received by mobile user $k\in\mathcal{K}$ is given by

$$\underbrace{\sum_{m\in\mathcal{M}}\mathbf{h}_{m,k}^{\mathsf{H}}\mathbf{w}_{m,k}s_k}_{\text{desired signal}}+\underbrace{\sum_{u\in\mathcal{K}\setminus\{k\}}\sum_{m\in\mathcal{M}}\mathbf{h}_{m,k}^{\mathsf{H}}\mathbf{w}_{m,u}s_u+n_k}_{\text{interfering signals}}, \tag{2}$$

where $\mathbf{h}_{m,k}\in\mathbb{C}^{N\times 1}$ denotes the downlink channel gain from the N antennas of RRH m to user k, and $n_k\sim\mathcal{CN}(0,\sigma_k^2)$ denotes the noise at user k with power σ_k^2. Thus, the SINR at user k is given by

$$\gamma_k=\frac{\left|\sum_{m\in\mathcal{M}}\mathbf{h}_{m,k}^{\mathsf{H}}\mathbf{w}_{m,k}\right|^2}{I_k+\sigma_k^2}, \tag{3}$$

where $I_k=\sum_{u\in\mathcal{K}\setminus\{k\}}\left|\sum_{m\in\mathcal{M}}\mathbf{h}_{m,k}^{\mathsf{H}}\,\mathbf{w}_{m,u}\right|^2$ denotes the interference power received by user k.

For MVNOs, providing high QoE to customers is important. However, since QoE evaluates the acceptability of applications from the perspective of mobile users subjectively, it is difficult to be used as a design criterion for the real-time resource allocation. Since QoE is closely related to QoS [10], [11], the QoE of mobile users can be enhanced by improving their QoS. Furthermore, sigmoidal functions have been widely adopted to model the QoS of mobile users by taking their received SINR as the input parameter [12]. Therefore, we use the sum of sigmoidal functions with the received SINR at mobile users to model the utility of network resources leased by the MVNO. In particular, QoS of a user not only depends on its received SINR but also depends on the type of mobile application. For simplicity, we assume that each user executes a single application on its UE. The case where multiple applications are running on a single UE can be modeled by defining multiple virtual UEs at the same location where each of them runs a single application. Let g_k denote the QoS of mobile user $k\in\mathcal{K}$. We use the following sigmoidal function to model the QoS of mobile user k with the received SINR γ_k:

$$g_k=\frac{1}{1+\exp\big(-a_k(\gamma_k-b_k)\big)}, \tag{4}$$

where constant parameters $a_k,b_k>0$ depend on the application run on the UE of mobile user k. We assume that parameters a_k and b_k are known by the MVNO.

III. Problem Formulation and Proposed Algorithm

We now formulate our problem and present the solution.

A. Problem Formulation

To improve the QoE of mobile user served by an MVNO, we propose to maximize the aggregate weighted QoS of these mobile users. Hence, we formulate the following optimization problem for the MVNO serving mobile users in set $\mathcal{K}$:

$$\underset{\mathbf{w}}{\text{maximize}} \ \sum_{k\in\mathcal{K}} \eta_k g_k \tag{5a}$$

$$\text{subject to} \ \sum_{k\in\mathcal{K}} \|\mathbf{w}_{m,k}\|^2 \le p_m, \ \forall\, m\in\mathcal{M}, \tag{5b}$$

where $\mathbf{w} \triangleq \left[\mathbf{w}_{1,1}^{\mathsf{H}} \dots \mathbf{w}_{M,1}^{\mathsf{H}} \dots \mathbf{w}_{1,K}^{\mathsf{H}} \dots \mathbf{w}_{M,K}^{\mathsf{H}}\right]^{\mathsf{H}}$ is the optimization variable and $\eta_k > 0$ is the weighting factor for mobile user $k \in \mathcal{K}$. Problem (5) cannot be easily solved because its objective function is non-convex. As a first step for solving problem (5), we introduce an interference threshold I for each mobile user in set $\mathcal{K}$. Hence, we include the following constraint in problem (5):

$$\sum_{u\in\mathcal{K}\setminus\{k\}} \left| \sum_{m\in\mathcal{M}} \mathbf{h}_{m,k}^{\mathsf{H}} \mathbf{w}_{m,u} \right|^2 \le I, \ \ \forall\, k\in\mathcal{K}, \tag{6}$$

where I is a predefined upper bound on the interference experienced by each mobile user. It should be noted that I is not an optimization variable in our proposed scheme. However, we will show that a suitable value of I can be obtained via off-line simulations. Including the additional constraint (6) has two benefits. First, the MVNO can control the amount of interference experienced by its customers. Second, we can decouple the interference mitigation from the objective function. A similar technique has also been used in [13]. We now define

$$\widetilde{g}_k \triangleq \frac{1}{1+\exp(-a_k(\widetilde{\gamma}_k - b_k))}, \tag{7}$$

where $\widetilde{\gamma}_k = \frac{\left|\sum_{m\in\mathcal{M}} \mathbf{h}_{m,k}^{\mathsf{H}} \mathbf{w}_{m,k}\right|^2}{I+\sigma_k^2}$ is a lower bound for γ_k in (3). This leads to the following optimization problem:

$$\underset{\mathbf{w}}{\text{maximize}} \ \sum_{k\in\mathcal{K}} \eta_k \widetilde{g}_k \tag{8a}$$

$$\text{subject to constraints (5b), (6).} \tag{8b}$$

Problem (8) is still non-convex since the objective function (8a) is in sum-of-ratios form. Hence, we transform it into an equivalent subtractive form by the following theorem.

Theorem 1: If beamforming vector $\mathbf{w}^\star = \left[\mathbf{w}_{1,1}^{\star\mathsf{H}} \dots \mathbf{w}_{M,K}^{\star\mathsf{H}}\right]^{\mathsf{H}}$ is the optimal solution to problem (8), there exist two vectors $\boldsymbol{\mu}^\star = (\mu_1^\star, \dots, \mu_K^\star)$ and $\boldsymbol{\beta}^\star = (\beta_1^\star, \dots, \beta_K^\star)$ such that vector $\mathbf{w}^\star$ is also an optimal solution of the problem in (9) as follows:

$$\underset{\mathbf{w}}{\text{maximize}} \sum_{k\in\mathcal{K}} \mu_k^\star \Big(\eta_k - \beta_k^\star \Big(1+\exp\big(-a_k\left(\widetilde{\gamma}_k - b_k\right)\big)\Big)\Big) \tag{9a}$$

$$\text{subject to constraints (5b), (6).} \tag{9b}$$

Moreover, $\mathbf{w}^\star$ satisfies the following system of equations:

$$\beta_k^\star \Big(1+\exp\big(-a_k(\widetilde{\gamma}_k^\star - b_k)\big)\Big) - \eta_k = 0, \tag{10a}$$

$$\mu_k^\star \Big(1+\exp\big(-a_k(\widetilde{\gamma}_k^\star - b_k)\big)\Big) - 1 = 0, \tag{10b}$$

where $\widetilde{\gamma}_k^\star = \frac{\left|\sum_{m\in\mathcal{M}} \mathbf{h}_{m,k}^{\mathsf{H}} \mathbf{w}_{m,k}^\star\right|^2}{I+\sigma_k^2}$.

Proof: Please refer to [14], [15] for a proof of Theorem 1. ■

Theorem 1 reveals that problem (8), which has an objective function in sum-of-ratios form, and problem (9), which has an objective function in subtractive form with parameters $(\boldsymbol{\mu}^\star, \boldsymbol{\beta}^\star)$, have the same $\mathbf{w}^\star$ as their optimal solution. Thus, problem (8) can be tackled by solving two nested problems in an iterative manner. Problem (9) is the inner problem for a given pair of parameter vectors $(\boldsymbol{\mu}, \boldsymbol{\beta})$. In the outer problem, we determine the right parameters $(\boldsymbol{\mu}^\star, \boldsymbol{\beta}^\star)$ that satisfy the system of equations in (10). The iterative algorithm to solve problem (8) is explained in detail in the next two subsections.

B. Inner Problem

For a given pair of vectors $\boldsymbol{\mu} = (\mu_1, \dots, \mu_K)$ and $\boldsymbol{\beta} = (\beta_1, \dots, \beta_K)$, the inner problem is formulated as follows:

$$\underset{\mathbf{w}}{\text{maximize}} \sum_{k\in\mathcal{K}} \mu_k \Big(\eta_k - \beta_k \Big(1+\exp\big(-a_k\left(\widetilde{\gamma}_k - b_k\right)\big)\Big)\Big) \tag{11a}$$

$$\text{subject to constraints (5b), (6).} \tag{11b}$$

We now transform problem (11) into a rank-constrained semidefinite programming (SDP) form. To this end, we define $\mathbf{w}_k \triangleq \left[\mathbf{w}_{1,k}^{\mathsf{H}} \ \dots \mathbf{w}_{M,k}^{\mathsf{H}}\right]^{\mathsf{H}}$, $\mathbf{h}_k \triangleq \left[\mathbf{h}_{1,k}^{\mathsf{H}} \dots \mathbf{h}_{M,k}^{\mathsf{H}}\right]^{\mathsf{H}}$, $\mathbf{W}_k \triangleq \mathbf{w}_k \mathbf{w}_k^{\mathsf{H}}$, $\mathbf{H}_k \triangleq \mathbf{h}_k \mathbf{h}_k^{\mathsf{H}}$, $\forall\, k \in \mathcal{K}$, and $\mathbf{J}_m \triangleq \mathsf{diag}(\mathbf{0}_{m-1}, 1, \mathbf{0}_{M-m}) \otimes \mathbf{I}_N$, $\forall\, m \in \mathcal{M}$. Then, problem (11) can be transformed into the following problem:

$$\underset{\boldsymbol{\tau}, \mathbf{W}_{\mathcal{K}}}{\text{maximize}} \sum_{k\in\mathcal{K}} \mu_k \Big(\eta_k - \beta_k \Big(1+\exp\big(-a_k(\tau_k - b_k)\big)\Big)\Big) \tag{12a}$$

$$\text{subject to} \sum_{k\in\mathcal{K}} \mathsf{Tr}(\mathbf{J}_m \mathbf{W}_k) \le p_m, \qquad \forall\, m\in\mathcal{M}, \tag{12b}$$

$$\sum_{u\in\mathcal{K}\setminus\{k\}} \mathsf{Tr}(\mathbf{H}_k \mathbf{W}_u) \le I, \qquad \forall\, k\in\mathcal{K}, \tag{12c}$$

$$\tau_k \le \frac{\mathsf{Tr}(\mathbf{H}_k \mathbf{W}_k)}{I+\sigma_k^2}, \qquad \forall\, k\in\mathcal{K}, \tag{12d}$$

$$\mathsf{Rank}(\mathbf{W}_k) \le 1, \qquad \forall\, k\in\mathcal{K}, \tag{12e}$$

$$\mathbf{W}_k \succeq \mathbf{0}, \qquad \forall\, k\in\mathcal{K}, \tag{12f}$$

where the optimization variables are given by $\mathbf{W}_{\mathcal{K}} \triangleq \left\{\mathbf{W}_k \,|\, k\in\mathcal{K}\right\}$ and $\boldsymbol{\tau} \triangleq (\tau_1, \dots, \tau_K)$, and p_m is the maximum transmission power of RRH $m \in \mathcal{M}$. Problem (12) is still non-convex due to constraint (12e). To achieve a tractable problem formulation, we relax constraint (12e) by removing it from problem (12). Then, we show the tightness of this relaxation for problem (12) in the following theorem.

Theorem 2: We denote $\left\{\boldsymbol{\tau}^\star, \mathbf{W}_{\mathcal{K}}^\star\right\}$ as the optimal solution of the problem in (13) as follows:

$$\underset{\boldsymbol{\tau}, \mathbf{W}_{\mathcal{K}}}{\text{maximize}} \sum_{k\in\mathcal{K}} \mu_k \Big(\eta_k - \beta_k \Big(1+\exp\big(-a_k\left(\tau_k - b_k\right)\big)\Big)\Big) \\ \text{subject to constraints (12b)–(12d), (12f).} \tag{13}$$

Then, the optimal solution $\left\{\boldsymbol{\tau}^\star, \overline{\mathbf{W}}_{\mathcal{K}}^\star\right\}$ for problem (12) can always be constructed with $\mathsf{Rank}\big(\overline{\mathbf{W}}_k^\star\big) \le 1$, $\forall\, k \in \mathcal{K}$.

Proof: Please refer to Appendix A for a proof of Theorem 2. ■

Theorem 2 reveals that after solving problem (13) and obtaining solution $\{\boldsymbol{\tau}^\star, \mathbf{W}_{\mathcal{K}}^\star\}$, if a matrix in $\mathbf{W}_{\mathcal{K}}^\star$ has its rank greater than 1, we can construct solution $\{\boldsymbol{\tau}^\star, \overline{\mathbf{W}}_{\mathcal{K}}^\star\}$ for problem (12) by solving another problem in SDP form.

C. Outer Problem

We denote the vectors of $\boldsymbol{\beta}$ and $\boldsymbol{\mu}$ that are applied for the inner problem (13) in the i^{th} iteration as $\boldsymbol{\beta}^{(i)}$ and $\boldsymbol{\mu}^{(i)}$, respectively. Moreover, we denote the solution of problem (13) when vectors $\boldsymbol{\beta}^{(i)}$ and $\boldsymbol{\mu}^{(i)}$ are employed as $\{\boldsymbol{\tau}^{(i)}, \mathbf{W}_{\mathcal{K}}^{(i)}\}$. We now define the following $2K$ functions for the i^{th} iteration:

$$\varphi_k^{(i)}(\beta_k^{(i)}) \triangleq \beta_k^{(i)}\Big(1+\exp\big(-a_k(\tau_k^{(i)}-b_k)\big)\Big)-\eta_k, \quad \text{(14a)}$$

$$\varphi_{K+k}^{(i)}(\mu_k^{(i)}) \triangleq \mu_k^{(i)}\Big(1+\exp\big(-a_k(\tau_k^{(i)}-b_k)\big)\Big)-1, \quad \text{(14b)}$$

where $k \in \mathcal{K}$. According to Theorem 1, the set of vectors $(\boldsymbol{\beta}^\star, \boldsymbol{\mu}^\star) = (\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)})$ is the unique set of parameters that we have employed in Theorem 1 if the $2K \times 1$ vector defined by $\boldsymbol{\varphi}^{(i)}\big(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)}\big) \triangleq \big(\varphi_1^{(i)}(\beta_1^{(i)}), \ldots, \varphi_K^{(i)}(\beta_K^{(i)}), \varphi_{K+1}^{(i)}(\mu_1^{(i)}), \ldots, \varphi_{2K}^{(i)}(\mu_K^{(i)})\big)$ satisfies the equality $\boldsymbol{\varphi}^{(i)}\big(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)}\big) = \mathbf{0}$. If $\boldsymbol{\varphi}^{(i)}\big(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)}\big) \neq \mathbf{0}$, we update $\big(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)}\big)$ by Newton's method to determine a new pair of vectors that will be used in the $(i{+}1)^{\text{th}}$ iteration. Specifically, we update $\big(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)}\big)$ as

$$\boldsymbol{\beta}^{(i+1)} = \boldsymbol{\beta}^{(i)} + \zeta^{(i)}\boldsymbol{\nu}_{1:K}^{(i)}, \quad \text{(15a)}$$

$$\boldsymbol{\mu}^{(i+1)} = \boldsymbol{\mu}^{(i)} + \zeta^{(i)}\boldsymbol{\nu}_{K+1:2K}^{(i)}, \quad \text{(15b)}$$

where vector $\boldsymbol{\nu}^{(i)} \triangleq -\big(\boldsymbol{\varphi}'(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)})\big)^{-1}\boldsymbol{\varphi}^{(i)}\big(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)}\big)$ and $\boldsymbol{\varphi}'\big(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)}\big)$ is the Jacobian matrix of $\boldsymbol{\varphi}^{(i)}\big(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)}\big)$. $\zeta^{(i)}$ takes the largest value of t^ℓ with $t \in (0,1)$ and $\ell = 1, 2, \ldots$ such that the following inequality holds:

$$\begin{aligned}\big\|\boldsymbol{\varphi}^{(i)}\big(\boldsymbol{\beta}^{(i)}{+}\xi^\ell\boldsymbol{\nu}_{1:K}^{(i)}, \boldsymbol{\mu}^{(i)}{+}\xi^\ell\boldsymbol{\nu}_{K+1:2K}^{(i)}\big)\big\| \\ \le (1{-}\epsilon\xi^\ell)\big\|\boldsymbol{\varphi}^{(i)}\big(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)}\big)\big\|,\end{aligned} \quad \text{(16)}$$

where $\epsilon \in (0,1)$ is a predefined parameter.

We want to highlight that when we update the pair of vectors $\big(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)}\big)$ in iteration i, we do not need to determine the corresponding rank-one matrices and restore the optimal beamforming vector for problem (11) by eigendecomposition. We can directly use the vector $\boldsymbol{\tau}^{(i)}$ achieved with beamforming matrices in set $\mathbf{W}_{\mathcal{K}}^{(i)}$ to obtain new parameter vectors $\big(\boldsymbol{\beta}^{(i+1)}, \boldsymbol{\mu}^{(i+1)}\big)$ in (15), since Theorem 2 reveals that the same vector $\boldsymbol{\tau}^{(i)}$ can be obtained by the rank-one matrices corresponding to the matrices in set $\mathbf{W}_{\mathcal{K}}^{(i)}$.

The proposed iterative algorithm to solve problem (8) is summarized in Algorithm 1. We denote $R_{\max}$ as the maximum number of iterations and Δ as the loop termination threshold. Both $R_{\max}$ and Δ, as well as the interference threshold I and the parameters ξ, ϵ employed in (16) are initialized in Step 1. In each iteration i (Steps 2–13), we first solve problem (13) in SDP form by using vectors $\big(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)}\big)$ to obtain solution $\{\boldsymbol{\tau}^{(i)}, \mathbf{W}_{\mathcal{K}}^{(i)}\}$ for the inner problem (Step 3). We then determine vector $\boldsymbol{\varphi}^{(i)}\big(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)}\big)$ (Step 4). If the norm of vector $\boldsymbol{\varphi}^{(i)}\big(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)}\big)$ is within a threshold Δ, we assign $\tau^{(i)}$ and $\mathbf{W}_{\mathcal{K}}^{(i)}$ to $\tau^\star$ and $\mathbf{W}_{\mathcal{K}}^\star$, respectively, and then break the loop (Steps 6 and 7). Otherwise, we use the maximum step size $\zeta^{(i)}$ (Step 11) to determine vectors $\big(\boldsymbol{\beta}^{(i+1)}, \boldsymbol{\mu}^{(i+1)}\big)$ for the $(i+1)^{\text{th}}$ iteration (Step 12). If the norm of vector $\boldsymbol{\varphi}^{(i)}\big(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)}\big)$ is always greater than the threshold Δ in all $R_{\max}$ iterations, the loop stops as well and we have $\mathbf{W}_{\mathcal{K}}^\star = \mathbf{W}_{\mathcal{K}}^{(R_{\max})}$. We first construct solution $\{\boldsymbol{\tau}^\star, \overline{\mathbf{W}}_{\mathcal{K}}^\star\}$ which satisfies the rank-one constraints according to Theorem 2 (Step 14). We then use eigendecomposition to obtain the principle eigenvector of matrix $\overline{\mathbf{W}}_k^\star \in \overline{\mathbf{W}}_{\mathcal{K}}^\star$ as the beamforming vector to serve mobile user k, $\forall\, k \in \mathcal{K}$ (Step 15).

Algorithm 1: Algorithm to solve problem (8).

1 **Initialize** $R_{\max}$, Δ, I, ξ, ϵ, $i := 1$, $(\boldsymbol{\beta}^{(1)}, \boldsymbol{\mu}^{(1)}) := \mathbf{1}_{2K}$.
2 **while** $(i \le R_{\max})$ **do**
3   Solve the inner problem by SDP after substituting $(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)})$ into problem (13) to obtain $\{\boldsymbol{\tau}^{(i)}, \mathbf{W}_{\mathcal{K}}^{(i)}\}$.
4   Determine the vector $\boldsymbol{\varphi}^{(i)}\big(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)}\big)$ using (14).
5   **if** $\big\|\boldsymbol{\varphi}^{(i)}\big(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)}\big)\big\| \le \Delta$ **then**
6   Set $\boldsymbol{\tau}^\star := \boldsymbol{\tau}^{(i)}$, $\mathbf{W}_{\mathcal{K}}^\star := \mathbf{W}_{\mathcal{K}}^{(i)}$.
7   **break**
8   **else**
9   Determine the Jacobian matrix $\boldsymbol{\varphi}'\big(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)}\big)$ of $\boldsymbol{\varphi}^{(i)}\big(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)}\big)$.
10   Set $\boldsymbol{\nu}^{(i)} := -\big(\boldsymbol{\varphi}'(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)})\big)^{-1}\boldsymbol{\varphi}^{(i)}\big(\boldsymbol{\beta}^{(i)}, \boldsymbol{\mu}^{(i)}\big)$.
11   Set $\zeta^{(i)} :=$ the largest ξ^ℓ that satisfies (16).
12   Set $\big(\boldsymbol{\beta}^{(i+1)}, \boldsymbol{\mu}^{(i+1)}\big) := \big(\boldsymbol{\beta}^{(i)}{+}\zeta^{(i)}\boldsymbol{\nu}_{1:K}^{(i)}, \boldsymbol{\mu}^{(i)}{+}\zeta^{(i)}\boldsymbol{\nu}_{K+1:2K}^{(i)}\big)$.
13   Set $\boldsymbol{\tau}^\star := \boldsymbol{\tau}^{(i)}$, $\mathbf{W}_{\mathcal{K}}^\star := \mathbf{W}_{\mathcal{K}}^{(i)}$, $i := i+1$.
14 Construct the solution $\{\boldsymbol{\tau}^\star, \overline{\mathbf{W}}_{\mathcal{K}}^\star\}$ which satisfies the rank-one constraints according to Theorem 2.
15 Employ beamforming vector $\mathbf{w}_k^\star$, which is the principal eigenvector of matrix $\overline{\mathbf{W}}_k^\star \in \overline{\mathbf{W}}_{\mathcal{K}}^\star$, to serve user k, $\forall\, k \in \mathcal{K}$.

TABLE I
SIMULATION PARAMETERS

Square area	$4\,\mathrm{km}^2$
Reference distance	$6\,\mathrm{m}$
User distribution	uniformly distributed in square area
Path loss exponent	3.8
Fading distribution	Rayleigh fading
Bandwidth	$20\,\mathrm{MHz}$
Number of antennas per RRH	4
ξ, ϵ, and $R_{\max}$ in Algorithm 1	0.9, 0.5, and 10 respectively
η_k, $\forall\, k \in \mathcal{K}$	uniformly distributed on $[1, 10]$
a_k, $\forall\, k \in \mathcal{K}$	inverse uniform distribution on $[\frac{5}{8}, 4]$
b_k, $\forall\, k \in \mathcal{K}$	$\frac{5}{a_k}$
σ_k^2, $\forall\, k \in \mathcal{K}$	$-101\,\mathrm{dBm}$

IV. SIMULATION RESULTS

In this section, we study the performance of the proposed scheme. We assume that several RRHs and a number of mobile users are located in a square area. Important simulation parameters are summarized in Table I. In particular, we assume each mobile user $k \in \mathcal{K}$ experiences the same noise power given by $\sigma_k^2 = -174\,\mathrm{dBm} + 10\log_{10}\big(20 \times 10^6\,\mathrm{Hz}\big) = -101\,\mathrm{dBm}$. For parameters a_k and b_k, we assume that the value of the SINR at which a mobile user achieves $\frac{1}{1+\exp(-5)} \times 100\% = 99.33\%$ of its maximum achievable QoS is uniformly distributed on $[2.5, 16]$. Thus, we set a_k by a random variable that follows

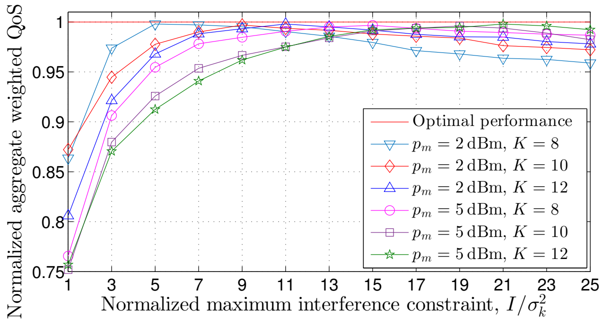

Fig. 2. With a suitable interference threshold I, the proposed algorithm achieves almost the same performance as an exhaustive search.

the inverse uniform distribution on the interval $[\frac{5}{8}, 4]$ and set $b_k = \frac{5}{a_k}, \forall k \in \mathcal{K}$. The parameter with different values in our simulation settings will be specified later.

We first show that a suitable interference threshold I in constraint (6) can be obtained off-line such that the optimal solution of the problem in (8) is close to the optimal solution of the problem in (5). In our simulations, 4 RRHs are used to serve different numbers of mobile users. Given the number of mobile users K and the transmission power p_m in a simulation scenario, we first obtain the optimal system performance for problem (5) by an exhaustive search. Then for each considered scenario, we set Δ in Algorithm 1 to be 0.01 and set the interference threshold I equal to a multiple of the noise power σ_k^2 in the simulation. Besides, we normalize the performance obtained in each simulation by the optimal performance in the considered scenario. The normalized performance is given in Fig. 2. The horizontal line at 1 represents the optimal performance obtained by solving problem (5) with exhaustive search. It is observed from Fig. 2 that Algorithm 1 can achieve almost optimal performance in the considered scenarios by choosing suitable interference thresholds I and solving problem (8). We also find by simulations that only a fraction of the time used by exhaustive search is actually required by Algorithm 1 to obtain the close-to-optimal performance.

We further conduct two sets of simulations to show that our proposed scheme achieves a higher aggregate weighted QoS than the traditional scheme that maximizes the weighted system sum rate. For comparison, we determine the beamforming vectors that maximize the weighted system sum rate by solving problem (5) but with the new objective function $\sum_{k\in\mathcal{K}} \eta_k \log_2(1+\gamma_k)$. This problem can be solved with a similar approach as developed in this paper by introducing an interference threshold I' for the maximal weighted system sum rate. We then use the optimal beamforming vectors that maximize the weighted system sum rate to determine the corresponding aggregate weighted QoS as a reference for the performance improvement.

In the first set of simulations, we use $M = 4$ RRHs with transmit power $p_m = 2$ dBm to serve different numbers of mobile users. The simulation results of the aggregate weighted QoS achieved by Algorithm 1 with different values of termination threshold Δ as well as the scheme that maximizes the weighted system sum rate are shown in Fig. 3. We observe

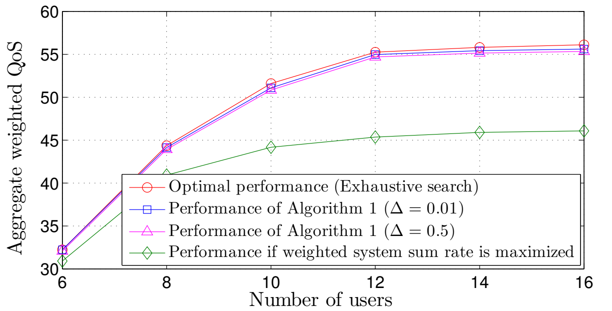

Fig. 3. Aggregate weighted QoS vs. the number of users ($M = 4$, $p_m = 2$ dBm).

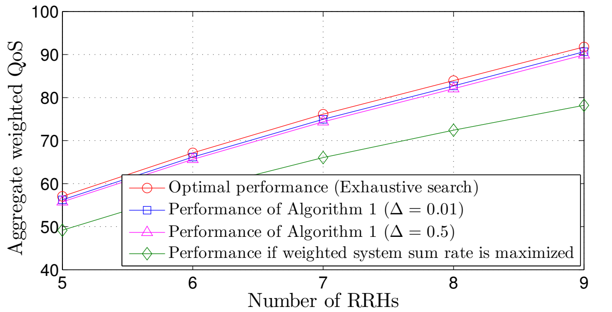

Fig. 4. Aggregate weighted QoS vs. the number of RRHs ($K = 20$, $p_m = 5$ dBm).

that the performance of the proposed algorithm is close to the optimal performance achieved by an exhaustive search. Moreover, similar performance can be obtained by running Algorithm 1 with $\Delta = 0.01$ and $\Delta = 0.5$. Compared to the case where the weighted system sum rate is maximized, our proposed scheme can increase the aggregate weighted QoS for mobile users. Specifically, the more mobile users are present in the system, the higher the performance gain. We also observe that the aggregate weighted QoS saturates for large numbers of users due to the limited network resources.

For the second set of simulations, we assume that there are 20 mobile users and show in Fig. 4 the aggregate weighted QoS as a function of the number of RRHs. In particular, we vary the number of RRHs from 5 to 9 and set transmission power $p_m = 5$ dBm. We find that the performance of the proposed algorithm is close to the optimal performance. Moreover, the performances obtained by Algorithm 1 with $\Delta = 0.01$ and $\Delta = 0.5$ are close. Also, it can be seen from Fig. 4 that the aggregate weighted QoS increases linearly with the number of RRHs in the system. The aggregate weighted QoS can also be increased compared to the case of maximizing the weighted system sum rate.

V. Conclusions

In this paper, we proposed to improve the QoE of mobile users by maximizing their aggregate weighted QoS. We modeled the QoS of each mobile user by a sigmoidal function and formulated the resource allocation algorithm design as a non-convex optimization problem. To solve this difficult problem, we first limited the multi-user interference by introducing an interference threshold and adding interference constraints.

We then transformed the objective function from sum-of-ratios form into a subtractive form, which led to a tractable optimization problem that could be solved by an iterative algorithm. Our simulation results have shown that adopting a suitable interference threshold enables the proposed algorithm to achieve a close-to-optimal performance. Simulation results also showed that the proposed beamforming design can improve the aggregate weighted QoS compared to the case when the weighted system sum rate is maximized. In the future work, we will consider the capacity-limited backhaul in C-RAN and the imperfection in CSI estimation. Furthermore, we will also propose a heuristic algorithm to future reduce the computational complexity of Algorithm 1 in this paper.

Appendix A: Proof of Theorem 2

Suppose the optimal solution $\{\boldsymbol{\tau}^\star, \mathbf{W}_{\mathcal{K}}^\star\}$ for problem (13) has been obtained and $\exists\, k \in \mathcal{K}$ with $\mathsf{Rank}(\mathbf{W}_k^\star) > 1$, we can obtain the optimal solution for problem (12) as follows. We first solve the following problem:

$$\underset{\mathbf{W}_{\mathcal{K}}}{\text{minimize}} \sum_{k\in\mathcal{K}} \mathsf{Tr}(\mathbf{W}_k) \tag{17a}$$

$$\text{subject to } \tau_k^\star \le \frac{\mathsf{Tr}(\mathbf{H}_k\mathbf{W}_k)}{I+\sigma_k^2}, \qquad \forall\, k \in \mathcal{K}, \tag{17b}$$

$$\text{constraints (12b)–(12d), (12f).}$$

Problem (17) is in SDP form, which is given by substituting $\boldsymbol{\tau}^\star$ into problem (13). Let $\overline{\mathbf{W}}_{\mathcal{K}}^\star$ denote the optimal solution of problem (17). It is easy to show that solution $\{\boldsymbol{\tau}^\star, \overline{\mathbf{W}}_{\mathcal{K}}^\star\}$ satisfies the constraints in problem (13) and obtains the same objective value as solution $\{\boldsymbol{\tau}^\star, \mathbf{W}_{\mathcal{K}}^\star\}$ for problem (13). We now show that $\mathsf{Rank}(\overline{\mathbf{W}}_k^\star) \le 1,\ \forall\, k \in \mathcal{K}$. The Lagrangian of problem (17) is

$$\mathcal{L}(\mathbf{W}_{\mathcal{K}}, \boldsymbol{\lambda}, \boldsymbol{\theta}, \boldsymbol{\rho}, \mathbf{S}_{\mathcal{K}}) = \sum_{k\in\mathcal{K}} \mathsf{Tr}\left(\left(\mathbf{A}_k - \frac{\rho_k\mathbf{H}_k}{I+\sigma_k^2} - \mathbf{S}_k\right)\mathbf{W}_k\right) + \Gamma,$$

where $\mathbf{A}_k \triangleq \mathbf{I}_{MN} + \sum_{m\in\mathcal{M}} \lambda_m \mathbf{J}_m + \sum_{u\in\mathcal{K}\setminus\{k\}} \theta_u \mathbf{H}_u$, and Γ contains the terms involving any constants and variables that are independent from $\mathbf{W}_{\mathcal{K}}$. The dual variables $\boldsymbol{\lambda}$, $\boldsymbol{\theta}$, $\boldsymbol{\rho}$, and $\mathbf{S}_{\mathcal{K}} \triangleq \{\mathbf{S}_k \,|\, k \in \mathcal{K}\}$ correspond to constraints (12b), (12c), (12d), and (12f), respectively. Thus, we have $\boldsymbol{\lambda}, \boldsymbol{\theta}, \boldsymbol{\rho} \succeq \mathbf{0}$, and $\mathbf{S}_k \succeq \mathbf{0}, \forall\, k \in \mathcal{K}$. The dual problem of (13) is given by

$$\underset{\boldsymbol{\lambda},\boldsymbol{\theta},\boldsymbol{\rho},\mathbf{S}_{\mathcal{K}}\succeq\mathbf{0}}{\text{minimize}} \ \sup_{\mathbf{W}_{\mathcal{K}}} \mathcal{L}(\mathbf{W}_{\mathcal{K}}, \boldsymbol{\lambda}, \boldsymbol{\theta}, \boldsymbol{\rho}, \mathbf{S}_{\mathcal{K}}). \tag{18}$$

The Karush-Kuhn-Tucker (KKT) conditions of problem (17) are given as follows:

$$\boldsymbol{\lambda}^\star, \boldsymbol{\theta}^\star \succeq \mathbf{0}, \tag{19a}$$

$$\boldsymbol{\rho}^\star \succeq \mathbf{0}, \tag{19b}$$

$$\mathbf{S}_k^\star \succeq \mathbf{0}, \qquad \forall\, k \in \mathcal{K}, \tag{19c}$$

$$\mathbf{S}_k^\star \overline{\mathbf{W}}_k^\star = \mathbf{0}, \qquad \forall\, k \in \mathcal{K}, \tag{19d}$$

$$\mathbf{S}_k^\star = \mathbf{A}_k^\star - \frac{\rho_k^\star \mathbf{H}_k}{I+\sigma_k^2}, \ \forall\, k \in \mathcal{K}, \tag{19e}$$

where $\mathbf{A}_k^\star$ is obtained by substituting the optimal dual variables into its definition. By jointly considering (19d) and (19e), we have the following equivalence relation:

$$\mathbf{S}_k^\star \overline{\mathbf{W}}_k^\star = \mathbf{0} \Leftrightarrow \mathbf{A}_k^\star \overline{\mathbf{W}}_k^\star = \frac{\rho_k^\star \mathbf{H}_k}{I+\sigma_k^2} \overline{\mathbf{W}}_k^\star \ \ \forall\, k \in \mathcal{K}. \tag{20}$$

Furthermore, by considering the inequalities in (19a), we have $\mathbf{A}_k^\star \succ \mathbf{0}$, $\forall\, k \in \mathcal{K}$. Thus, we have $\mathsf{Rank}(\mathbf{A}_k^\star) = MN$, $\forall\, k \in \mathcal{K}$. Therefore, for all $k \in \mathcal{K}$, we have

$$\begin{aligned}\mathsf{Rank}(\overline{\mathbf{W}}_k^\star) &= \mathsf{Rank}(\mathbf{A}_k^\star \overline{\mathbf{W}}_k^\star) \\ &= \mathsf{Rank}\left(\frac{\rho_k^\star \mathbf{H}_k}{I+\sigma_k^2}\overline{\mathbf{W}}_k^\star\right) \\ &\le \min\left\{\mathsf{Rank}\left(\frac{\rho_k^\star \mathbf{H}_k}{I+\sigma_k^2}\right), \mathsf{Rank}(\overline{\mathbf{W}}_k^\star)\right\}.\end{aligned}$$

By considering (19b), we have $\mathsf{Rank}\big(\frac{\rho_k^\star \mathbf{H}_k}{I+\sigma_k^2}\big) \le 1$. Thus, we have $\mathsf{Rank}(\overline{\mathbf{W}}_k^\star) \le 1$. That is, by solving problem (17) with vector $\boldsymbol{\tau}^\star$ in the solution $\{\boldsymbol{\tau}^\star, \mathbf{W}_{\mathcal{K}}^\star\}$ of problem (13), we can always construct optimal solution $\{\boldsymbol{\tau}^\star, \overline{\mathbf{W}}_{\mathcal{K}}^\star\}$ for problem (12) with $\mathsf{Rank}(\overline{\mathbf{W}}_k^\star) \le 1$, $\forall\, k \in \mathcal{K}$. This completes the proof. ■

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