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Multiobjective Optimization for Energy Efficiency in Cloud Radio Access Networks

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Abstract
In this paper our goal is to optimize the energy efficiency (EE) of massive multi-input multi-output (MU-MIMO) systems through Cloud Radio Access Network (C-RAN). First we obtain the maximum energy efficiency with four user association algorithms, named nearest-based user association (NBUA), full user association, multi-candidate RRHs user association (MCRUA), and improved (MCRUA), respectively. Then we consider a multiple-objective optimization approach (MOOP) which is non -convex. Pareto solution using weighted Tchebycheff method is proposed to convert MOOP into equivalent single-objective optimization problem (SOOP). The simulation results show comparisons of the four user association algorithms in which the improved MCRUA achieves higher performance.
Keywords - Multiobjective optimization, Pareto optimal, energy efficiency

I. INTRODUCTION

Cloud radio access network (C-RAN) has been introduced recently for high performance mobile and wireless network which are served by a large number of distributed antennas [1]. To balance the requirements of the increasing mobile terminals and wireless networks, C-RAN has been found an effective methodology to fulfil these requests [2, 3]. Also C-RAN includes cost effective architecture and deployment. In C-RAN, a baseband unit (BBU) is linked to all the deployed base stations (BSs) and BBUs are placed in the middle and linked with distributed remote radio heads (RRHs).

There are various studies devoted to half-duplex (HD) massive multi input multi output (MIMO) systems in the past. The base station is equipped with large number of antenna enabling massive MIMO type of architecture which provides better energy efficiency (EE) [1, 3]. However, multiobjective optimization and resource allocation in HD-CRAN is still limited in literature. In multiobjective approach, the optimization problem is generally a kind of non-convex fractional programming problem which is a bit difficult to solve [4]. Several studies have been done to deal with the fractional objective functions which transform them into an equivalent optimization problem via iterative approach. Selecting RRHs for each user as user association is a challenging task. In previous literatures, several user association algorithms have been studied such as nearest-RRH based user association (NBUA), multi-candidate RRHs user association (MCRUA), improved MCRUA, and full user association to deal these problems based on different planning metrics [5].

We examine the EE optimization problem in HD C-RAN scenario with the respect of the fronthaul compression. In this work, we propose the multiobjective EE optimization. To solve this non-convex problem, we apply two different steps. In first step, we adopt the Tchebycheff method which converts optimization problem into a single objective optimization problem (SOOP) [6,7]. Further in next step, iterative algorithm is applied based on the Dinkelbach method to find complete optimal solution [8]. Simulation outcomes show that our algorithm achieves good convergence speed. The results also show the performance comparisons of all different user association algorithms.

II. SYSTEM MODEL

Consider downlink (DL) C-RAN L cell network, in which N RRHs and K MU users are distributed in each cell uniformly. MU has a single antenna. We also assume that the n-th RRH in the j-th cell is equipped with $M_{j,n}$ antennas and the total number of system antennas is given by $\sum_{n=1}^{N} M_{j,n} = M_{\max}$.

The channel vector from the RRHs in the l-th cell to the k-th MU in the j-th cell is represented as

$$\mathbf{g}_{jkl} = \mathbf{\Lambda}_{jkl}^{1/2}\mathbf{h}_{jkl} \tag{1}$$

where $\mathbf{\Lambda}_{jkl} = \mathrm{diag}\left(\left[\lambda_{jkl1}, \dots, \lambda_{jklN}\right]^{\mathrm{T}}\right) \otimes \mathbf{I}_N$, $\lambda_{jkln} \triangleq ad_{jkln}^{-\alpha}$ and $\mathbf{h}_{jkln} = \left[\mathbf{h}_{jkl1}^{\mathrm{T}}, \dots, \mathbf{h}_{jklN}^{\mathrm{T}}\right]^{\mathrm{T}}$. Here λ_{jkln} is the path loss of channel, d_{jkln} is the distance between k -th MU in the j -th cell and n -th RRH in the l -th cell, $\otimes$ is the symbol for Kronecker product, a is the path loss gain, α is the path loss exponent. $\mathbf{h}_{jkln}$ is the M_{ln} x 1 small-scale fading channel vector which is independent and identically distributed and given by complex Gaussian distribution $\sim CN(0,1)$.

According to the minimum mean-square error (MMSE) estimation, the channel vector at BBU is given by $\hat{\mathbf{g}}_{jkl} = \mathbf{\Lambda}_{jkl}\mathbf{Q}_{jkl}^{-1}y_{\mathrm{P},jk}$ where $\mathbf{Q}_{jkl}^{-1} = \left(\sum_{1=l}^{L}\mathbf{\Lambda}_{jkl} + \sigma_{\mathbf{P}}^2\mathbf{I}_{\max}\right)$ and $y_{\mathbf{P},jk} = \sum_{1=i}^{L}\mathbf{g}_{jkl} + \mathbf{z}_{jk}$ is $M_{\max}$ x 1 received pilot signal. Here, the large-scale fading between the n-th RRH and k-th MU is given by $\beta_{jkl} = \mathbf{\Lambda}_{jkl}\left(\sum_{l=1}^{L}\mathbf{\Lambda}_{jkl} + \sigma_{\mathrm{P}}^2\right)^{-1/2}$. The receiver's additive white Gaussian noise vector $\mathbf{z}_{kl}$ is given by $CN(0, \sigma_{\mathbf{P}}^2\mathbf{I}_{\max})$. The channel vector can be decomposed as $\mathbf{g}_{jkl} = \tilde{\mathbf{g}}_{jkl} + \hat{\mathbf{g}}_{jkl}$ where $\hat{\mathbf{g}}_{jkl} \sim CN\left(0, \mathbf{\Lambda}_{jkl} - \mathbf{\Lambda}_{jkl}\mathbf{Q}_{jkl}^{-1}\mathbf{\Lambda}_{jkl}\right)$.

Following the principle of maximum ratio transmission in beamforming, the user association matrix A_j in the j-th cell is indicated by

$$a_{jkl} = \begin{cases} 1, \text{ if } \mathbf{w}_{jkl} = \hat{\mathbf{g}}_{jkl} & (n\text{-th RRH is associated with } k\text{-th user}) \\ 0, \text{ if } \mathbf{w}_{jkl} = 0 & (n\text{-th RRH is not associated with } k\text{-th user}) \end{cases} \tag{3}$$

The DL transmitted signal from all RRHs in the j-th cell is given as $\mathbf{x}_j = \sum_{k=1}^{K_{D,j}} \mathbf{w}_{jk}S_{jk}$, where $\mathbf{w}_{jk} = \left[\mathbf{w}_{jk1}^{\mathrm{T}}, \dots, \mathbf{w}_{jkN}^{\mathrm{T}}\right]^{\mathrm{T}}$ is the beamforming vector for sending data symbol $S_{jk} = \sqrt{p_{jk}u_{jk}}$ to k-th MU. Here u_{jk} is the data symbols. The received signal at the k-th MU in the j-th cell is expressed by

$$y_{jk} = \sum_{i=1}^{L} \sqrt{p_{jk}} \mathbf{g}_{jkl}^{H} x_l + \mathbf{z}_{jk} \quad (4)$$

where $\mathbf{z}_{jk}$ is the receiver noise at the k-th MU in the j-th cell given by $\mathbf{z}_{jk} \sim CN(0, \sigma)$. Hence, we can expressed the received DL signal to interference-plus-noise ratio (SINR) of the k-th MU in the j-th cell as

$$\gamma_{jk}\left(\mathbf{A}_j, \mathbf{m}_j, \mathbf{p}_j\right) = \frac{\left|\mathrm{E}\left[\sqrt{p_{jk}} \mathbf{g}_{jkl}^{\mathrm{H}} \hat{\mathbf{g}}_{jkl}\right]\right|^2}{\mathrm{var}\left[\sqrt{p_{jk}} \mathbf{g}_{jkl}^{\mathrm{H}} \hat{\mathbf{g}}_{jkl}\right] + \sum_{(l,i)\neq(j,k)} \left|\mathrm{E}\left[\sqrt{p_{li}} \mathbf{g}_{jkl}^{\mathrm{H}} \hat{\mathbf{g}}_{lil}\right]\right|^2 + \sigma^2} \quad (5)$$

$\mathbf{p}_j = [p_{j1}, p_{j2}, \ldots, p_{jK}]^{\mathrm{T}}$ is the transmit power between the RRHs to each MU in the j -th cell and $\mathbf{m}_j = [m_{j1}, m_{j2}, \ldots, m_{jN}]^{\mathrm{T}}$ signifies the number of active antennas at each RRH in the j-th cell. Therefore, we write the achievable rate in the j-th cell by

$$C_{jk}\left(\mathbf{A}_j, \mathbf{m}_j, \mathbf{p}_j\right) = B \log_2\left(1 + \gamma_{jk}\left(\mathbf{A}_j, \mathbf{m}_j, \mathbf{p}_j\right)\right) \quad (6)$$

where B is the bandwidth. Now, we calculate the total network power consumption in the j-th cell which is given by

$$P_{jk}\left(\mathbf{A}_j, \mathbf{m}_j, \mathbf{p}_j\right) = p_c \sum_{n=1}^{N} m_{jn} + \sum_{n=1}^{N} \sum_{k=1}^{K} p_{jk} a_{jk} + p_0 \quad (7)$$

where p_c is the power consumption per antenna which is independent of the transmit power. p_0 is the static power consumption at the RRH and BBU. Thus, by applying the achievable rate and the power consumption, the EE can be given by

$$EE_j\left(\mathbf{A}_j, \mathbf{m}_j, \mathbf{p}_j\right) = \frac{\sum_{k=1}^{K} C_{jk}\left(\mathbf{A}_j, \mathbf{m}_j, \mathbf{p}_j\right)}{P_j\left(\mathbf{A}_j, \mathbf{m}_j, \mathbf{p}_j\right)} \quad (8)$$

III. PROBLEM FORMULATION

Based on the above analysis, the problem to maximize the EE under maximum power and minimum data rate constraints can be formulated:

$$\max_{\mathbf{A}_j, \mathbf{m}_j, \mathbf{p}_j} \eta_j\left(\mathbf{A}_j, \mathbf{m}_j, \mathbf{p}_j\right) \quad (9)$$

$$\text{s.t. } C_{jk} \geq C_{\min}, \ \forall k \quad (10)$$

$$\sum_{k=1}^{K} p_{jk} \leq P_{\max} \quad (11)$$

$$1 \leq \sum_{n=1}^{N} a_{jkn} \leq N, \forall k \quad (12)$$

$$0 \leq m_{jn} \leq M_{\max} / N, \forall n \quad (13)$$

(10) implies the minimum data rate requirements and (11) represents the constraints for DL transmit powers. (12) is the constraint for the minimum number of MU association and (13) represents the constraint for the number of active antennas.

We are using four user association algorithms for improvement of EE called NBUA, full user association algorithm, MCRUA, and improved MCRUA. In NBUA algorithm, each user is associated with the single nearest RRH, and the RRHs which are not used are in sleep mode. In MCRUA algorithm, each user is associated with all RRH, and let the number of RRHs in active mode.

IV. THE PROPOSED ALGORITHM

The goal of our work is to optimize the EE for each user by joint bandwidth and power allocation. Therefore the optimizing problem can be expressed as

$$\max_{\mathbf{A}_j, \mathbf{m}_j, \mathbf{p}_j} \eta_{jk}\left(\mathbf{A}_j, \mathbf{m}_j, \mathbf{p}_j\right) \quad (14)$$

subject to (10)-(13).

We find the Pareto optimal of EE by converting the MOOP into a SOOP. We are using weighted Tchebycheff method [7, 8], in which we assign some set of weights. Comparing to other methods to MOOPs, with the weighted Tchebycheff method we get a best Pareto optimal set by changing the weights which is expressed as:

$$\max_{\mathbf{A}_j, \mathbf{m}_j, \mathbf{p}_j} \min_k \left\{\varphi_k \eta_{jk}^0 - \eta_{jk}\right\} \quad (15)$$

subject to (10)-(13). Here, $\emptyset = \{\emptyset_1, \ldots, \emptyset_K\}$ is a weight vector and η_{jk}^0 is the Utopia EE of user k. Moreover, since the objective function is quasiconvex, we can separate A_j from others to transfer in equivalent one.

$$\min_{\mathbf{m}_j, \mathbf{p}_j} \max_k \left\{\phi_{jk}\left(\frac{(\eta_{jk}^0 P_{jk}^{\mathrm{opt}} - C_{jk}^{\mathrm{opt}})}{P_{jk}}\right)\right\} \quad (16)$$

The objective function (16) is a class of fractional programming (FP), which minimizes the maximum of numerous fractions [11]. Now we are using the following process, to convert into quasiconvex and equivalent to [7],

$$\max_{v \in \mathrm{V}} \min_{\mathbf{m}_j, \mathbf{p}_j} f(\mathbf{v}, \mathbf{m}_j, \mathbf{p}_j) = \frac{\sum_{k=1}^{K} v_{jk} \phi_{jk} (\eta_k^0 P_{jk} - C_{jk})}{\sum_{k=1}^{K} v_{jk} P_{jk}} \quad (17)$$

where $\mathbf{V} \triangleq \left\{\left(\mathrm{v}_{j1}, \ldots, \mathrm{v}_{jK}\right) \middle| \mathrm{v}_{jk} \geq 0, \forall k, \sum_{k=1}^{K} \mathrm{v}_{jk} = 1\right\}$.

By an iterative algorithm, we solve the above problem summarized in Table 1.

Finding $\{\mathbf{m}_j, \mathbf{p}_j\}$ and optimal $\mathbf{v}$ can be obtained iteratively by sub problems $\eta(\mathbf{v}) = \min_{\mathbf{m}_j, \mathbf{p}_j} f(\mathbf{v}, \mathbf{m}_j, \mathbf{p}_j)$ and $\eta^* = \max_{v \in \mathbf{V}} \eta(\mathbf{v})$, respectively. A function F is defined as:

$$F(\mathbf{v}, \alpha) = \sum_{k=1}^{K} \mathbf{v}_{jk} \left(\phi_{jk}\left((\eta_{jk}^0 C_{jk} - P_{jk}) - \alpha P_{jk}\right)\right) \quad (18)$$

Let $\mathbf{v}^{(t)}$, $t = 0,1,...,$ be an order of sequence updated by the following equation

$$\mathbf{v}^{(t+1)} = \arg\max_{\mathbf{v}\in\mathrm{V}} \min_{\mathbf{m}_j,\mathbf{p}_j} F\left(\mathbf{v}, \eta\left(\mathbf{v}^{(t)}\right)\right) \tag{19}$$

Table 1. Joint Resource Allocation Algorithm

1. Initially set $v^0 \in \mathrm{V}$, and t=1,ε_1 and ε_2
2. solve $\mathbf{m}_j^{\mathrm{opt}}, \mathbf{p}_j^{\mathrm{opt}} = \arg\min_{\mathbf{m}_j,\mathbf{p}_j} F\left(\mathbf{v}^{(t)}, \eta\right)$
3. **If** $\left|\sum_{k=1}^{K} v_{jk}^{(t)} \varphi_{jk}\left(\eta_{jk}^{0} P_{jk}^{\mathrm{opt}} - \mathrm{C}_{jk}^{\mathrm{opt}}\right) - \eta P_{jk}^{\mathrm{opt}}\right| < \varepsilon_1,$
4. **goto** step (10).
5. **Else**
6. Update $\eta = \dfrac{\sum_{k=1}^{K} \mathbf{v}_{jk}^{(t)} \varphi_{jk}(\eta_{jk}^{0} P_{jk}^{\mathrm{opt}} - \mathrm{C}_{jk}^{\mathrm{opt}})}{\sum_{k=1}^{K} \mathbf{v}_{jk}^{(t)} P_{jk}^{\mathrm{opt}}}$.
7. **goto** step (2).
8. **end**
9. Update $\mathbf{v}^{(t+1)} = \arg\max_{\mathbf{v}\in\mathrm{V}} \min_{\mathbf{m}_j,\mathbf{p}_j} F\left(\mathbf{v}, \eta\left(\mathbf{v}^{(t)}\right)\right)$
10. **If** $\eta\left(\mathbf{v}^{(t+1)}\right) - \eta\left(\mathbf{v}^{(t)}\right) < \varepsilon_2$, **then**
11. set $\eta^{\mathrm{opt}} = \eta\left(\mathbf{v}^{(t)}\right)$.
12. **exit**.
13. **else**
14. set $t = t+1$.
15. **until** convergence of η_{jk}
16. **return** $\eta_{jk}^{\mathrm{opt}} = \eta_{jk}^{(t)}$
17. **goto** step (2).
18. **End**

Finally, (a) $\eta(\mathbf{v})$ is obtained when $\min_{\mathbf{m}_j,\mathbf{p}_j} F(\mathbf{v}, \eta(\mathbf{v})) = 0.$

(b) $\eta^{\mathrm{opt}} = \eta(\mathbf{v}^{(t)})$ is obtained when $\eta(\mathbf{v}^{(t+1)}) = \eta(\mathbf{v}^{(t)})$.

Here the Dinkelbach method is used to find the optimization solution until the total EE performance is converged.

V. SIMULATION RESULTS

In this section, we compare the various user association algorithms. We adopt 7-cell network. Each cell has N= 15 RRH and K=20 MU. We also consider the parameter of power consumption p_c =1W, P_{max}=1mW, $p_0 = 10$W. Bandwidth B is 20 MHz, the noise parameter σ^2 is -120dBm, and path loss coefficient α is 4.

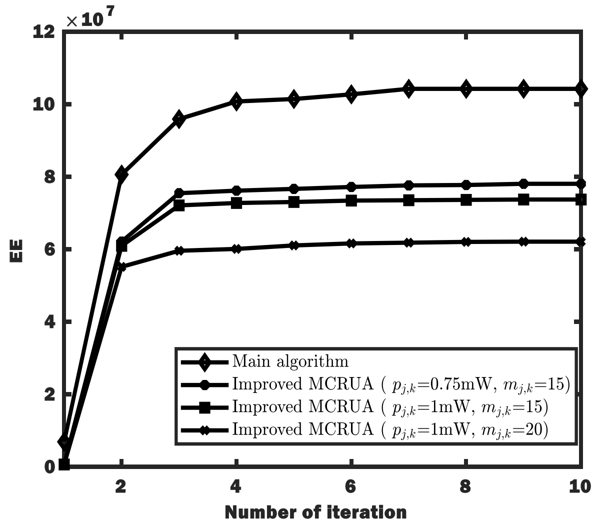

Figure 1. Energy efficiency versus number of iteration.

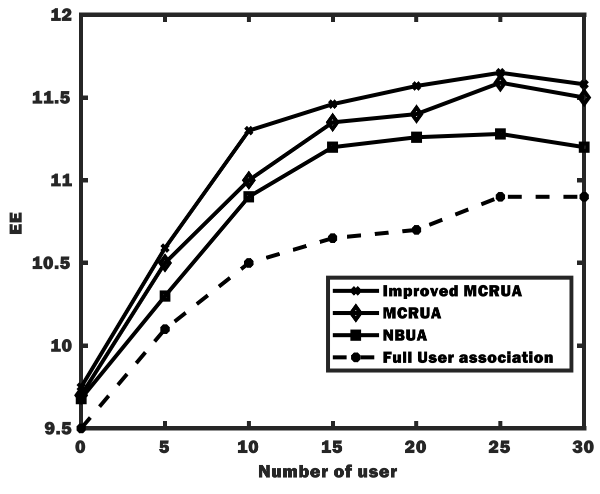

Figure 2. Energy efficiency versus K

Fig. 1 shows performance of EE versus iteration number. The proposed algorithm is compared with improved MCRUA for various active antennas and transmits power constraints. It is noticeable that the proposed pareto optimal algorithm has a fast convergence and achieves a higher EE.

Fig. 2 shows the performances of EE using four user association algorithms with different number of users K. The number of RRHs is 10. One can see the optimal number of users to have the maximum EE.

VI. CONCLUSION

In this paper, we considered a multiobjective optimization of energy efficient joint resource allocation algorithm. We first achieved Pareto optimal solution of the energy efficiency using weighted Tchebycheff method which convers MOOP into of single objective into equivalent single-objective optimization problem (SOOP). The simulation results show comparisons of the four user association algorithms in which the improved MCRUA algorithm has a superior energy efficiency when the number of users is large.

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