Energy Efficient Joint Resource Allocation for Multi-cell C-RAN System

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Abstract
In this paper, we propose a joint resource allocation algorithm for energy efficiency (EE) of a cloud radio access network (C-RAN). To tackle the joint optimization problem, we utilize a successive convex approximation (SCA) based joint antenna selection and power allocation (JASPA) algorithm. In addition, we propose an improved multi-candidate remote radio heads (RRHs) user association (MCRUA) algorithm. The simulation results reveal that for a C-RAN, we can achieve a significant gain in the EE of the proposed joint resource allocation.

INTRODUCTION
Cloud radio access network (C-RAN) has been considered for fifth-generation (5G) mobile networks due to high spectral efficiency and energy efficiency (EE) [1]. In C-RAN, the baseband unit (BBU) is located in the center of a cell, and is connected to remote radio heads (RRHs). The basic idea of the C-RAN is that the transmission distance between antennas and mobile users (MUs) is reduced, so that significant improvement to the EE are achieved. From the viewpoint of green information technology, the EE has recently attracted more attention. Thus, the resource allocation for EE maximization has attracted considerable attention. However, most existing works on resource allocation for the EE of C-RAN consider the separated optimization problems. In this paper, we maximize the downlink EE in C-RAN by solving a joint resource allocation optimization problem. To tackle the complex joint optimization problem, we utilize a successive convex approximation (SCA) based joint antenna selection and power allocation (JASPA) algorithm [2]. Furthermore, we propose an improved multi-candidate RRHs user association (MCRUA) algorithm. This algorithm utilizes the tabu search technique [3-4] to obtain the appropriate large-scale fading threshold (LSFT) for EE improvement. Finally, a joint resource allocation algorithm with fast convergence is proposed, which is based on the Dinkelbach method [5] for solving nonlinear fractional problems.

SYSTEM MODEL
We consider a C-RAN system with \( L \) hexagonal cells, where each cell has \( N \) RRHs. In each cell, \( K \) single antenna MUs are uniformly distributed. We also assume that the \( n \)-th RRH in the \( j \)-th cell is equipped with \( M_j \) antennas and the total number of system antennas in the \( j \)-th cell is given by \( \sum_{n=1}^{N} M_j = M_{\text{sys}} \).

The channel vector between the RRHs in the \( i \)-th cell and the \( k \)-th MU in the \( j \)-th cell is denoted as \( \mathbf{g}_{jk} = \mathbf{A}_{jk}^{1/2} \mathbf{h}_{jk} \) where \( \mathbf{A}_{jk}^{1/2} = \text{diag}(\lambda_{jk,1}, \ldots, \lambda_{jk,L}^{1/2}) \mathbf{I}_K \) and \( \lambda_{jk,B} \triangleq \alpha d_{jk}^{-\alpha} s_{jk} \). \( \mathbf{h}_{jk} = [h_{jk,1}^*, \ldots, h_{jk,L}^*]^T \). Here, \( \lambda_{jk,B} \) represents the long-term path loss between the \( k \)-th MU in the \( j \)-th cell and the \( n \)-th RRH in the \( i \)-th cell. \( \mathbf{I}_K \) represents the Kronecker product, \( \alpha \) is the path loss gain, and \( \alpha \) is the path loss exponent. \( \mathbf{h}_{jk,B} \) denotes an \( M_{\text{sys}} \times 1 \) small-scale fading channel vector which contains independent and identically distributed circularly symmetric complex Gaussian random variables with zero mean and unit variance.

The minimum mean-square error channel estimation for the channel vector is given by \( \hat{\mathbf{g}}_{jk} = \mathbf{A}_{jk}^{1/2} \mathbf{Q}_{jk} \mathbf{y}_{jk} \) and \( \mathbf{y}_{jk} = \sum_{l=1}^{L} \mathbf{g}_{jk,l}^T + \mathbf{z}_{jk} \) is \( M_{\text{sys}} \times 1 \) received pilot signal. Here, the large-scale fading between the \( n \)-th RRH in the \( l \)-th cell and the \( k \)-th MU in the \( j \)-th cell is given by \( \beta_{jk} = \lambda_{jk,B} \left( \sum_{l=1}^{L} \lambda_{jk,l} + \sigma_v^2 \right)^{-1/2} \). The receiver’s additive white Gaussian noise vector \( \mathbf{z}_{jk} \) is \( \mathcal{CN}(0, \sigma_v^2 \mathbf{I}_{M_{\text{sys}}}) \). The channel vector \( \mathbf{g}_{jk} \) can be decomposed as \( \mathbf{g}_{jk} = \tilde{\mathbf{g}}_{jk} + \mathbf{g}_{jk,B} \) where \( \tilde{\mathbf{g}}_{jk} \sim \mathcal{CN}(0, \mathbf{A}_{jk} - \mathbf{A}_{jk} \mathbf{Q}_{jk}^{-1} \mathbf{A}_{jk}) \).

We employed maximum ratio transmission beamforming, and the user association matrix \( \mathbf{A}_j \) in the \( j \)-th cell is denoted as

\[
a_{jk,n} = \begin{cases} 1, & \text{if } \mathbf{w}_{jk,n} = \hat{\mathbf{h}}_{jk,n}, \text{ (n-th RRH is associated with k-th user)} \\ 0, & \text{if } \mathbf{w}_{jk,n} = 0, \text{ (n-th RRH is not associated with k-th user)} \end{cases}
\]

(1)

The downlink transmitted signal from all RRHs in the \( j \)-th cell is expressed as \( \mathbf{x}_j = \sum_{k=1}^{K} \mathbf{w}_{jk} s_{jk} \) where \( \mathbf{w}_{jk} = [\mathbf{w}_{jk,1}^T, \ldots, \mathbf{w}_{jk,K}^T]^T \) is the beamforming vector used to send data signal \( s_{jk} = \sqrt{P_{jk} u_{jk}} \) to \( k \)-th MU. Here \( u_{jk} \) represents the data symbols. The received signal at the \( k \)-th MU in the \( j \)-th cell is given by

\[
\mathbf{y}_{jk} = \mathbf{H}_{jk} \mathbf{x}_j + \mathbf{N}_{jk} + \mathbf{n}_{jk,B} + \mathbf{n}_{jk}
\]
\[ y_j = \sum_{i=1}^{l} \sqrt{p_j g_{ji}^n} x_i + z_j \]  \hspace{1cm} (2)

where \( z_j \) is the receiver noise at the \( k \)-th MU in the \( j \)-th cell, and is given by \( z_j \sim CN(0, \sigma^2) \). Thus, the downlink signal-to-interference-plus-noise ratio for \( k \)-th MU in the \( j \)-th cell is written as

\[ \gamma_j(A_j, m_j, p_j) = \frac{\mathbb{E}\left[ \sum_{i \neq j} \sqrt{p_j g_{ji}^n} x_i \right]^2}{\text{var} \left[ \sum_{i \neq j} \sqrt{p_j g_{ji}^n} x_i \right]} + \sigma^2 \]  \hspace{1cm} (3)

where \( p_j = [p_{j1}, p_{j2}, \ldots, p_{jk}]^T \) is the transmit power from the RRHs to each MU in the \( j \)-th cell, and \( m_j = [m_{j1}, m_{j2}, \ldots, m_{jk}]^T \) denotes the number of active antennas at each RRH in the \( j \)-th cell.

The achievable rate in the downlink of the \( k \)-th MU in the \( j \)-th cell is written as

\[ C_j(A_j, m_j, p_j) = B \log_2 \left( 1 + \gamma_j(A_j, m_j, p_j) \right) \]  \hspace{1cm} (4)

where \( B \) is the bandwidth. Then, we describe the total network power consumption in the \( j \)-th cell as follows

\[ P_j(A_j, m_j, p_j) = p_j \sum_{n=1}^{N} m_{jn} + \sum_{k=1}^{K} p_j a_{jk} + p_0 \]  \hspace{1cm} (5)

where \( p_j \) is the circuit power consumption per antenna, which is independent of the transmit power. \( p_0 \) is the basic power consumption at the RRH and BBU. Thus, the system EE is given by

\[ \eta_j(A_j, m_j, p_j) = \frac{\sum_{k=1}^{K} C_j(A_j, m_j, p_j)}{P_j(A_j, m_j, p_j)} \]  \hspace{1cm} (6)

**PROBLEM FORMULATION**

In this paper, the optimization problem aims to maximize the system EE as follows

\[ \max_{A_j, m_j, p_j} \eta_j(A_j, m_j, p_j) \]  \hspace{1cm} (7)

s.t \( C_j \geq C_{\text{min}}, \forall k \)  \hspace{1cm} (8)

\[ \sum_{k=1}^{K} p_j \leq P_{\text{max}} \]  \hspace{1cm} (9)

\[ 1 \leq \sum_{n=1}^{N} a_{jk} \leq N, \forall k \]  \hspace{1cm} (10)

\[ 0 \leq m_{jn} \leq M_{\text{max}} / N, \forall n \]  \hspace{1cm} (11)

(8) implies the minimum data rate requirements and (9) represents the constraints for downlink transmit powers. (10) is the constraint for the minimum number of MU association and (11) represents the constraint for the number of active antennas.

**EE MAXIMIZATION ALGORITHM**

In this section, we describe the proposed joint resource allocation algorithm to maximize EE. This main algorithm consists of two sub-algorithms, which are named as Algorithm 1 and 2. Algorithm 1 is for the optimization of JASPA and Algorithm 2 is for the optimization of user association.

In Algorithm 1, we fix \( A_j \) and solve problem (7) to obtain \( m_j \) and \( p_j \) by using the SCA technique to approximate the objective function based on (12).

\[ \log(1 + \omega_{jk}) \geq f(\omega_{jk}, a_{jk}, b_{jk}) = a_{jk} \omega_{jk} + b_{jk} \]  \hspace{1cm} (12)

where \( a_{jk} \) and \( b_{jk} \) are adaptively calculated variables, which can be chosen as

\[ a_{jk} = \frac{\omega_{jk}}{1 + \omega_{jk}}; \quad b_{jk} = \log(1 + \omega_{jk}) - \frac{\omega_{jk} \log \omega_{jk}}{1 + \omega_{jk}} \]  \hspace{1cm} (13)

Because of the above convexity approximation, we apply this lower bound approximation \( \tilde{C}_{jk} = \log(1 + r_{jk}) \), where \( \omega_{jk} \) corresponds to \( r_{jk} \). We also replace the variables \( \hat{m}_j = \log m_j \) and \( \hat{p}_j = \log p_j \) to employ the approximated optimization problem. Applying \( \tilde{C}_{jk}(\hat{m}_j, \hat{p}_j, a_{jk}, b_{jk}) = f(\gamma_{jk}(\hat{m}_j, \hat{p}_j), a_{jk}, b_{jk}) \) and \( \hat{P}_j(\hat{m}_j, \hat{p}_j) \) in (7), the approximated optimization problem of (7) becomes a convex problem due to the concave objective function.

**Table. 1 Algorithm 1 SCA-based JASPA**

1: Initially set \( a^{(0)} = 1, b^{(0)} = 0 \), and \( t = 1 \)
2: repeat
3: Solve the approximation problem of (7) to obtain \( m_j^{(t)}, p_j^{(t)} \)
4: Compute \( \gamma_j(A_j, m_j^{(t)}, p_j^{(t)}) \) and update \( a^{(t)}, b^{(t)} \) from (13)
5: \( t = t + 1 \)
6: until Convergence of \( (m_j^{(t)}, p_j^{(t)}) \)
7: return \( (m_j^{(T)}, p_j^{(T)}) = (m_j^{(t)}, p_j^{(t)}) \)

For given \( m_j \) and \( p_j \), we obtain an optimal \( A_j \) in Algorithm 2. In this algorithm, the \( k \)-th MU is associated with the \( n \)-th RRH when large-scale fading between \( k \)-th MU and \( n \)-th RRH is larger than an LSFT. The basic idea of the improved MCRUA is to search an optimal LSFT by applying a tabu search. First, we divide the LSFT range into \( S \) sections, and we search for the local optimal value in each section. Then, we derive the optimum value using these local optimal values. This algorithm also iteratively searches the minimum active RRHs until the system’s EE is converged. The RRH that serves the minimal number of MUs is the inefficient RRH. In Algorithm 2, the inefficient RRH is iteratively switched into sleep mode. Thus, the improved MCRUA is a more efficient algorithm than the conventional MCRUA which uses the predefined LSFT.
Table 2. Algorithm 2 Improved MCRUA

1: Initially set feasible LSFT $\frac{\beta^{(s)}}{\nu}$ and $t = 1$
2: repeat
3: for $n = 1, 2, \ldots, N$
4: for $s = 1, 2, \ldots, S$
5: while Convergence of $\eta^{(s)}(A^{(s)}, m_j, p_j)$
6: $a_{jn} = 1$ if $B_{jn} \geq \frac{\beta^{(s)}}{\nu}$ and compute $\eta^{(s)}(A^{(s)}, m_j, p_j)$
7: Search for optimal $\frac{\gamma^{(s)}}{\nu}$ to maximize $\eta^{(s)}(A^{(s)}, m_j, p_j)$
8: end while
9: end for
10: $\bar{\gamma} = \text{arg max}_{s} \eta^{(s)}(A^{(s)}, m_j, p_j)$ and $A^{\text{Opt}} = A^{(\bar{\gamma})}$
11: end for
12: Compute $\eta^{(s)}(A^{(s)}, m_j, p_j)$ and update $A^{(s)} = A^{\text{Opt}}$
13: Search for the inefficient $n$-th RRH and $a_{jn} = 0, \forall k$
14: $t = t + 1$
15: until Convergence of $A^{(s)}$
16: return $A^{\text{Opt}} = A^{(t)}$

Applying Algorithm 1 and 2, we constructed the main algorithm based on the Dinkelbach method. The main algorithm, namely Algorithm 3, optimizes $A_j$, $m_j$, $p_j$ until the total EE performance is converged.

Table 3. Algorithm 3 Main Algorithm

1: Initially set $t = 1$
2: repeat
3: Use Algorithm 1 to obtain $(\mathbf{m}^{\text{Opt}}, \mathbf{p}^{\text{Opt}})$
4: Update $(\mathbf{m}^{(s)}, \mathbf{p}^{(s)}) = (\mathbf{m}^{\text{Opt}}, \mathbf{p}^{\text{Opt}})$
5: Use Algorithm 2 to obtain $A^{\text{Opt}}$
6: Update $A^{(s)} = A^{\text{Opt}}$
7: until Convergence of $\eta_j(A^{(s)}, m^{(s)}, p^{(s)})$
8: return $\eta_j(A^{\text{Opt}}, m^{\text{Opt}}, p^{\text{Opt}}) = \eta_j(A^{(s)}, m^{(s)}, p^{(s)})$

SIMULATION RESULTS

We assumed that the C-RAN system is composed of $L = 7$ hexagonal cells, where each cell has $N = 7$ RRHs and $K = 15$ MUs. In each cell, the total number of system antennas is given by $M_{\text{max}} = 140$. We set the power parameter $P_{\text{max}} = 1\text{mW}$, $p_1 = 1\text{W}$, and $p_0 = 10\text{W}$. The noise parameter $\sigma_2$ and $\sigma_p^2$ are all -120 dBm and the path-loss exponent $\alpha$ is 4.

Fig. 1 compares the system EE of various user association schemes. Full association implies that all MU are associated with all RRHs in each cell. Nearest RRH, Nearest-based user association (NBUA), and MCRUA are the user association schemes which are referred in [6]. The simulation results show that the proposed improved MCRUA algorithm achieves a higher EE performance than the other user association schemes.

Fig. 2 shows the system EE versus the iteration number. The proposed joint resource allocation is compared with the improved MCRUA for various active antennas and transmit power constraints. One can see that the proposed joint resource allocation algorithm achieves a higher EE than applying only Algorithm 2.

CONCLUSION

In this paper, we proposed an energy efficient joint resource allocation algorithm for C-RAN. To tackle the joint resource allocation, we employed an SCA-based JASPA and proposed an improved MCRUA. The simulation results show that the proposed algorithm always converges after several iterations. Further, the simulation results reveal that it is possible to achieve a significant gain in the EE of the proposed joint resource allocation algorithm for C-RAN.
REFERENCES


