Energy-Efficient Coordinated Beamforming with Individual Data Rate Constraints

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***Abstract*—Coordinated beamforming has been optimized to maximize the sum rate under the transmit power constraints, or to minimize the transmit power under the data rate constraints. In this paper, we study coordinated beamforming to maximize the energy efficiency (EE) of multi-cell multi-antenna systems meanwhile ensuring the individual data rate requirement of each user. To find a solution of the non-convex optimization problem for the precoding design, we construct a convex subset of the original constraint set and a quasi-concave lower bound of the EE. Then, we propose an iterative algorithm to maximize the lower bound of the EE within the convex subset. We evaluate the EE of the proposed algorithm through simulations under different data rate requirements, user locations, and cell-edge signal-to-noise ratios. The results demonstrate that the proposed precoder is much more energy-efficient than the transmit power minimization precoder when the circuit power consumption dominates, and always outperforms two interference-free transmission schemes with the optimized transmit power toward maximizing the EE.**

I. Introduction

Inter-cell interference (ICI) is the major limiting factor for improving spectrum efficiency (SE) of multi-cell multi-input-multi-output (MIMO) systems. Coordinated multi-point coordinated beamforming (CoMP-CB) is an effective approach to mitigate the ICI. Toward the goal of supporting different services, the optimal precoding designs for CoMP-CB to maximize the sum rate under the transmit power constraints [1] and to minimize the transmit power under the quality of service (QoS) constraints [2] have been considered.

To reduce the operational cost of the networks and the global greenhouse gas emissions, energy efficiency (EE) is becoming an important design goal for cellular systems [3]. Recently, it has been recognized that the design for providing high SE (e.g., [1]) does not necessarily provide high EE [4]. In fact, the design that minimizes the transmit power (say, [2]) is not always energy-efficient when the circuit power consumption is taken into account.

The basic principle of energy-efficient design is maximizing the EE of the system without sacrificing the required QoS of the users. Different kinds of traffics impose different QoS constraints, e.g., some need a constant data rate while the others require to complete transmission within a hard deadline. For multi-cell MIMO systems, an energy-efficient precoding including both transmit beamforming and power allocation without any QoS constraints was proposed in [5], which is applicable to the best effort traffics.

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In this paper, we study the precoding to maximize the EE of CoMP-CB system considering the QoS provisions. Specifically, we strive to optimize the precoding consisting of beamforming and power allocation that maximizes the EE under the minimal data rate requirement of each user, where both the transmit power and circuit power consumption are taken into account. By setting the values of the data rate requirement, different classes of the traffics including the best effort and real and non-real time services can be accommodated [6]. Because both the objective function and constraints are non-convex, the optimization problem is non-convex. To find a solution of the problem, we construct a convex subset of the original constraint set and a quasi-concave lower bound of the objective function. Then, we propose an iterative algorithm to maximize the lower bound within the convex subset. Simulation results show that the proposed precoding is more energy-efficient than the transmit power minimization precoding [2] in a wide range of data rate requirement.

Notation: The superscript $(\cdot)^H$ denotes the Hermitian transpose of a matrix. The $n \times n$ identity matrix is denoted by $\mathbf{I}_n$. The complex Gaussian distribution is denoted by $\mathcal{CN}(\cdot,\cdot)$. The symbols $\mathbb{E}(\cdot)$, $\mathrm{Tr}(\cdot)$, and $\det(\cdot)$ denote expectation, trace, and determinant operators, respectively.

II. System Model and Problem Formulation

Consider a K-cell CoMP-CB system, where K base stations (BSs) transmit to multiple users in a coordinated manner. The k-th BS, which needs to convey data to I_k users, is equipped with M_k antennas. The i-th user in cell k, user i_k, is equipped with N_{i_k} antennas. We assume that every BS has perfect channel information from itself to all the users.

The signal received at user i_k can be expressed as

$$\mathbf{y}_{i_k} = \mathbf{H}_{i_k k}\mathbf{V}_{i_k}\mathbf{x}_{i_k} + \sum_{m=1, m\neq i}^{I_k} \mathbf{H}_{i_k k}\mathbf{V}_{m_k}\mathbf{x}_{m_k} + \sum_{j\neq k, j=1}^{K}\sum_{l=1}^{I_j}\mathbf{H}_{i_k j}\mathbf{V}_{l_j}\mathbf{x}_{l_j} + \mathbf{n}_{i_k}, \quad \forall i_k \in \mathcal{I} \qquad (1)$$

where $\mathbf{x}_{i_k}$ is the signal vector of size d_{i_k} transmitted to user i_k with $\mathbb{E}[\mathbf{x}_{i_k}\mathbf{x}_{i_k}^H] = \mathbf{I}_{d_{i_k}}$, $\mathbf{V}_{i_k}$ is the $M_k \times d_{i_k}$ precoding matrix with the beamforming and power allocation implicitly included, $\mathbf{H}_{i_kj}$ is the $N_{i_k} \times M_j$ channel matrix between BS j and user i_k, $\mathcal{I} = \{i_k | i \in \{1, 2, \ldots, I_k\}, \quad k \in \{1, 2, \ldots, K\}\}$ is the set of all users, and $\mathbf{n}_{i_k}$ is an additive white Gaussian noise vector subject to $\mathcal{CN}(0, \sigma_{i_k}^2 \mathbf{I}_{N_{i_k}})$.

Define $\mathbf{J}_{i_k} = \sum_{(l,j)\neq(i,k)} \mathbf{H}_{i_kj}\mathbf{V}_{l_j}\mathbf{V}_{l_j}^H\mathbf{H}_{i_kj}^H + \sigma_{i_k}^2\mathbf{I}_{N_{i_k}}$ as the covariance matrix of the interference and noise. Then the data rate of user i_k can be expressed as [7],

$$R_{i_k} = \log_2 \det\left(\mathbf{I}_{N_{i_k}} + \mathbf{H}_{i_kk}\mathbf{V}_{i_k}\mathbf{V}_{i_k}^H\mathbf{H}_{i_kk}^H\mathbf{J}_{i_k}^{-1}\right). \quad (2)$$

The total power consumption of the system involves transmit power and circuit power consumption, which is

$$P = \sum_{k=1}^{K}\sum_{i=1}^{I_k} \rho \mathrm{Tr}(\mathbf{V}_{i_k}\mathbf{V}_{i_k}^H) + P_c, \quad (3)$$

where $\mathrm{Tr}(\mathbf{V}_{i_k}\mathbf{V}_{i_k}^H) = P_{i_k}$ is the transmit power for user i_k, ρ is the reciprocal of the power amplifier efficiency, and P_c is the circuit power consumption.

The EE is defined as the ratio of the sum rate and the total power consumption [3], which is

$$\eta(\mathbf{V}) = \frac{\sum_{k=1}^{K}\sum_{i=1}^{I_k} R_{i_k}}{P}, \quad (4)$$

where $\mathbf{V}$ is short for $\{\mathbf{V}_{i_k}\}_{i_k\in\mathcal{I}}$, which denotes all precoding matrices for the users in the K cells.

To find the precoders for all users that maximize the EE and ensure the minimal data rate requirement of each user, the optimization problem is formulated as

$$\max_{\mathbf{V}} \frac{\sum_{k=1}^{K}\sum_{i=1}^{I_k} \log_2\det\left(\mathbf{I}_{N_{i_k}} + \mathbf{H}_{i_kk}\mathbf{V}_{i_k}\mathbf{V}_{i_k}^H\mathbf{H}_{i_kk}^H\mathbf{J}_{i_k}^{-1}\right)}{\sum_{k=1}^{K}\sum_{i=1}^{I_k}\rho\mathrm{Tr}(\mathbf{V}_{i_k}\mathbf{V}_{i_k}^H) + P_c} \quad (5a)$$

$$\mathbf{s.t.}\ \log_2\det\left(\mathbf{I}_{N_{i_k}} + \mathbf{H}_{i_kk}\mathbf{V}_{i_k}\mathbf{V}_{i_k}^H\mathbf{H}_{i_kk}^H\mathbf{J}_{i_k}^{-1}\right) \geq r_{i_k}, \quad \forall i_k \in \mathcal{I} \quad (5b)$$

where r_{i_k} is the data rate requirement of user i_k.

III. Optimization Algorithm

Optimization problem (5) is non-convex, because the objective function is non-concave over $\mathbf{V}$ and the constraints are not convex [8]. To find a solution of the problem, we construct a convex subset of the original set of non-convex constraint (5b), and a lower bound of the EE that is a quasi-concave function of $\mathbf{V}$. Then, we propose an iterative algorithm to maximize the lower bound in the convex subset.

A. Convex Subset and Lower Bound

Note that the non-convexity of the problem comes from the non-convexity of the data rate in (2), which can be achieved by an optimal detection matrix at user i_k, i.e., maximal likelihood detector. Based on this observation, we first find a concave function that is a lower bound of the data rate by considering a linear detector. Then, we can construct a convex subset of (5b) and a quasi-concave lower bound of the EE.

Define a function of precoding matrices as follows,

$$f_{i_k}(\mathbf{V}, \mathbf{U}_{i_k}, \mathbf{W}_{i_k}) \triangleq \log_2 e \cdot (\ln\det(\mathbf{W}_{i_k}) - \mathrm{Tr}(\mathbf{W}_{i_k}\mathbf{E}_{i_k}) + d_{i_k}), \quad (6)$$

where $\mathbf{U}_{i_k}$ is a detection matrix at user i_k, $\mathbf{W}_{i_k}$ is an auxiliary positive definite matrix, e is the base of natural logarithms, and $\mathbf{E}_{i_k}$ is the mean-square-error (MSE) covariance matrix, i.e.,

$$\mathbf{E}_{i_k} = (\mathbf{I}_{d_{i_k}} - \mathbf{U}_{i_k}^H\mathbf{H}_{i_kk}\mathbf{V}_{i_k})(\mathbf{I}_{d_{i_k}} - \mathbf{U}_{i_k}^H\mathbf{H}_{i_kk}\mathbf{V}_{i_k})^H + \sum_{(l,j)\neq(i,k)} \mathbf{U}_{i_k}^H\mathbf{H}_{i_kj}\mathbf{V}_{l_j}\mathbf{V}_{l_j}^H\mathbf{H}_{i_kj}^H\mathbf{U}_{i_k} + \sigma_{i_k}^2\mathbf{U}_{i_k}^H\mathbf{U}_{i_k}. \quad (7)$$

Theorem 1: $f_{i_k}(\mathbf{V}, \mathbf{U}_{i_k}, \mathbf{W}_{i_k})$ is a lower bound of the data rate R_{i_k} and is concave over each of the matrices $\mathbf{V}, \mathbf{U}_{i_k}, \mathbf{W}_{i_k}$ when the other two are fixed.

Proof: First, we show that $f_{i_k}(\mathbf{V}, \mathbf{U}_{i_k}, \mathbf{W}_{i_k})$ is concave over $\mathbf{V}, \mathbf{U}_{i_k}, \mathbf{W}_{i_k}$, respectively. By substituting (7) into (6), we have

$$\begin{aligned}&\ln 2 \cdot f_{i_k}(\mathbf{V}, \mathbf{U}_{i_k}, \mathbf{W}_{i_k}) \\ &= \ln\det(\mathbf{W}_{i_k}) + d_{i_k} - \mathrm{Tr}(\sigma_{i_k}^2\mathbf{W}_{i_k}\mathbf{U}_{i_k}^H\mathbf{U}_{i_k}) \\ &\quad - \mathrm{Tr}(\mathbf{W}_{i_k}(\mathbf{I}_{d_{i_k}} - \mathbf{U}_{i_k}^H\mathbf{H}_{i_kk}\mathbf{V}_{i_k})(\mathbf{I}_{d_{i_k}} - \mathbf{U}_{i_k}^H\mathbf{H}_{i_kk}\mathbf{V}_{i_k})^H) \\ &\quad - \sum_{(l,j)\neq(i,k)} \mathrm{Tr}(\mathbf{W}_{i_k}\mathbf{U}_{i_k}^H\mathbf{H}_{i_kj}\mathbf{V}_{l_j}\mathbf{V}_{l_j}^H\mathbf{H}_{i_kj}^H\mathbf{U}_{i_k}),\end{aligned} \quad (8)$$

which is concave quadratic over $\mathbf{V}$ when $\mathbf{U}_{i_k}$ and $\mathbf{W}_{i_k}$ are fixed. Similarly, with fixed $\mathbf{V}$ and $\mathbf{W}_{i_k}$, it is concave quadratic over $\mathbf{U}_{i_k}$. With fixed $\mathbf{V}$ and $\mathbf{U}_{i_k}$, the MSE covariance matrix $\mathbf{E}_{i_k}$ is fixed and $f_{i_k}(\mathbf{V}, \mathbf{U}_{i_k}, \mathbf{W}_{i_k})$ is concave over $\mathbf{W}_{i_k}$.

Then, we prove that $f_{i_k}(\mathbf{V}, \mathbf{U}_{i_k}, \mathbf{W}_{i_k})$ is a lower bound of R_{i_k}. Actually, R_{i_k} is the maximum of $f_{i_k}(\mathbf{V}, \mathbf{U}_{i_k}, \mathbf{W}_{i_k})$, which can be proved by employing the minimum mean-square-error (MMSE) detector.

Given the precoding matrices $\mathbf{V}$, the trace of $\mathbf{E}_{i_k}$ is minimized when a MMSE detector is employed, which is

$$\mathbf{U}_{i_k}^* = \left(\sum_{j=1}^{K}\sum_{l=1}^{I_l}\mathbf{H}_{i_kj}\mathbf{V}_{l_j}\mathbf{V}_{l_j}^H\mathbf{H}_{i_kj}^H + \sigma_{i_k}^2\mathbf{I}_{N_{i_k}}\right)^{-1}\mathbf{H}_{i_kk}\mathbf{V}_{i_k}. \quad (9)$$

By substituting it into (6), we obtain

$$f_{i_k}(\mathbf{V}, \mathbf{U}_{i_k}^*, \mathbf{W}_{i_k}) = \log_2 e \cdot (\ln\det(\mathbf{W}_{i_k}) - \mathrm{Tr}(\mathbf{W}_{i_k}\mathbf{E}_{i_k}^*) + d_{i_k}), \quad (10)$$

where $\mathbf{E}_{i_k}^*$ is the MSE covariance matrix when $\mathbf{U}_{i_k}^*$ is used.

By taking the gradient of $f_{i_k}(\mathbf{V}, \mathbf{U}_{i_k}^*, \mathbf{W}_{i_k})$ over $\mathbf{W}_{i_k}$ and setting the gradient as $\mathbf{0}$, we obtain the optimal auxiliary matrix that maximizes the function in (10), which is

$$\mathbf{W}_{i_k}^* = (\mathbf{E}_{i_k}^*)^{-1}. \quad (11)$$

With $\mathbf{U}_{i_k}^*$ and $\mathbf{W}_{i_k}^*$, the maximum of the function in (6) is achieved, which is

$$f_{i_k}(\mathbf{V}, \mathbf{U}_{i_k}^*, \mathbf{W}_{i_k}^*) = \log_2\det\left((\mathbf{E}_{i_k}^*)^{-1}\right). \quad (12)$$

According to the relation between the MSE and signal-to-interference-plus-noise ratio [9], the expression in (12) is equal to the data rate in (2). This suggests that R_{i_k} is the maximum value of $f_{i_k}(\mathbf{V}, \mathbf{U}_{i_k}, \mathbf{W}_{i_k})$. In other words, $f_{i_k}(\mathbf{V}, \mathbf{U}_{i_k}, \mathbf{W}_{i_k})$ is a lower bound of the data rate R_{i_k}. ■

With the help of Theorem 1, we can construct a convex subset of constraint (5b) for any fixed $\mathbf{U}_{i_k}$ and $\mathbf{W}_{i_k}$ as

$$f_{i_k}(\mathbf{V}, \mathbf{U}_{i_k}, \mathbf{W}_{i_k}) \geq r_{i_k}, \ \forall i_k \in \mathcal{I}. \tag{13}$$

We can also find a lower bound of the objective function in (5a) for any fixed $\mathbf{U}_{i_k}$ and $\mathbf{W}_{i_k}$ as follows,

$$L(\mathbf{V}) \triangleq \frac{\sum_{k=1}^{K}\sum_{i=1}^{I_k} f_{i_k}(\mathbf{V}, \mathbf{U}_{i_k}, \mathbf{W}_{i_k})}{\sum_{k=1}^{K}\sum_{i=1}^{I_k} \rho \mathrm{Tr}(\mathbf{V}_{i_k}\mathbf{V}_{i_k}^H) + P_c}, \tag{14}$$

which is tight when $\mathbf{U}_{i_k} = \mathbf{U}_{i_k}^*$ and $\mathbf{W}_{i_k} = \mathbf{W}_{i_k}^*$.

The denominator in (14) is convex quadratic and the numerator is concave quadratic over $\mathbf{V}$ (see Theorem 1). Therefore, all the superlevel sets of (14)

$$\Theta_\alpha = \{\mathbf{V} \in \mathbf{dom}\ L | L(\mathbf{V}) \geq \alpha\}$$

are convex quadratic for any real number α. That is to say, $L(\mathbf{V})$ is quasi-concave over $\mathbf{V}$ with fixed $\mathbf{U}$ and $\mathbf{W}$ [8] [10], where $\mathbf{U}$ is short for $\{\mathbf{U}_{i_k}\}_{i_k \in \mathcal{I}}$ and $\mathbf{W}$ is short for $\{\mathbf{W}_{i_k}\}_{i_k \in \mathcal{I}}$.

Then, a new optimization problem that maximizes the EE lower bound can be formulated as follows,

$$\max_{\mathbf{V},\mathbf{U},\mathbf{W}} \frac{\sum_{k=1}^{K}\sum_{i=1}^{I_k} f_{i_k}(\mathbf{V}, \mathbf{U}_{i_k}, \mathbf{W}_{i_k})}{\sum_{k=1}^{K}\sum_{i=1}^{I_k} \rho \mathrm{Tr}(\mathbf{V}_{i_k}\mathbf{V}_{i_k}^H) + P_c} \quad \mathbf{s.t.} \quad (13) \tag{15}$$

which can be solved by an iterative algorithm proposed later.

B. Iterative Algorithm and Initial Value

We use the block coordinate descent method [11] to solve problem (15), i.e., fix two of the three matrices to update the third. We update $\mathbf{U}$ with (9) and $\mathbf{W}$ with (11). Since the objective function is quasi-concave over $\mathbf{V}$ with fixed $\mathbf{U}$ and $\mathbf{W}$, the update of $\mathbf{V}$ can be obtained by solving problem (15) with bisection algorithm [8].

Because the objective function of problem (5) is non-concave, there might be several local optima in the constraint set. This indicates that the solution of the proposed algorithm depends on the initial value. To find a good solution, we can start from many different initial values and choose the best solution. To reduce the complexity, we employ an energy-efficient interference alignment (IA) precoder optimized in the following as the initial value, which can provide fairly good performance as shown in Section IV.

The IA precoder that maximizes the EE is as follows. The transmit beamforming matrix $\mathbf{Q}_{i_k}$ and the detection matrix $\mathbf{D}_{i_k}$ for user i_k are designed jointly following IA principle to remove the interference, whose expressions can be found from [12] [13]. Then the achievable data rate is [14]

$$R_{i_k}^{IA} = \log_2 \det(\mathbf{I}_{d_{i_k}} + \frac{P_{i_k}}{d_{i_k}\sigma_{i_k}^2}\mathbf{G}_{i_k}\mathbf{G}_{i_k}^H), \tag{16}$$

where $\mathbf{G}_{i_k} = \mathbf{D}_{i_k}^H \mathbf{H}_{i_k k} \mathbf{Q}_{i_k}$.

We optimize the power allocation for each user to maximize the EE by formulating the following optimization problem,

$$\max_{P_{i_k}} \frac{\sum_{k=1}^{K}\sum_{i=1}^{I_k} \log_2 \det(\mathbf{I}_{d_{i_k}} + \frac{P_{i_k}}{d_{i_k}\sigma_{i_k}^2}\mathbf{G}_{i_k}\mathbf{G}_{i_k}^H)}{\sum_{k=1}^{K}\sum_{i=1}^{I_k} \rho P_{i_k} + P_c} \tag{17a}$$

$$\mathbf{s.t.} \ \log_2 \det(\mathbf{I}_{d_{i_k}} + \frac{P_{i_k}}{d_{i_k}\sigma_{i_k}^2}\mathbf{G}_{i_k}\mathbf{G}_{i_k}^H) \geq r_{i_k}, \ \forall i_k \in \mathcal{I}, \tag{17b}$$

whose solution $P_{i_k}^*$ can be found by Lagrangian techniques, because the objective function is pseudo-concave [15]. Then the energy-efficient IA precoder is

$$\mathbf{V}_{i_k}^{IA} = \sqrt{\frac{P_{i_k}^*}{d_{i_k}}}\mathbf{Q}_{i_k}, \forall i_k \in \mathcal{I}. \tag{18}$$

It is not hard to show that $\mathbf{V}_{i_k}^{IA}$ satisfies the constraint (13). Therefore, it can be used as an initial value of the proposed iterative algorithm. The proposed algorithm is summarized in Table 1 and it can be proved to converge to a stationary point of the original problem (5); however, due to the lack of space, we do not provide the proof for the convergence here.

TABLE I
PROCEDURE OF THE ITERATIVE ALGORITHM

1. Initialize $\mathbf{V}$ with (18).
2. Update $\mathbf{U}$ with (9).
3. Update $\mathbf{W}$ with (11).
4. Solve (15) with bisection algorithm to update $\mathbf{V}$.
5. Go back to Step 2 until convergence.

To better understand the proposed iterative algorithm, we illustrate its procedure in Fig. 1 and Fig. 2, which show the change of the convex subset and the quasi-concave EE lower bound with iterations. Given $\mathbf{U}^{(1)}$ and $\mathbf{W}^{(1)}$ that denote the matrices at the first iteration, by maximizing the lower bound $L_1(\mathbf{V})$ within the subset S_1, point A$(\mathbf{V}^{(1)}, \mathbf{U}^{(1)}, \mathbf{W}^{(1)})$ is obtained. Updating $\mathbf{U}$ and $\mathbf{W}$, we obtain a point B$(\mathbf{V}^{(1)}, \mathbf{U}^{(2)}, \mathbf{W}^{(2)})$ on the curve of the original non-concave function $\eta(\mathbf{V})$. In the next iteration, $L_2(\mathbf{V})$, the lower bound through point B within the subset S_2 is maximized, then we obtain point C$(\mathbf{V}^{(2)}, \mathbf{U}^{(2)}, \mathbf{W}^{(2)})$. We can see that the subset covers more and more regions of the original set of constraint (5b) and the gap between the lower bound of the EE and the original objective function diminishes with an increasing number of iterations. If $\mathbf{V}^{(2)}$ is a stationary point of $\eta(\mathbf{V})$ as shown in Fig. 2, by maximizing the lower bound $L_3(\mathbf{V})$ within the subset S_3, the iterative algorithm will converge to the point D$(\mathbf{V}^{(2)}, \mathbf{U}^{(3)}, \mathbf{W}^{(3)})$.

Such a procedure shows that the proposed iterative algorithm is different from the iteratively weighted MMSE approach in [9] where the constraint set is convex and remains unchanged with iterations; besides, our objective function also differs from that in [9].

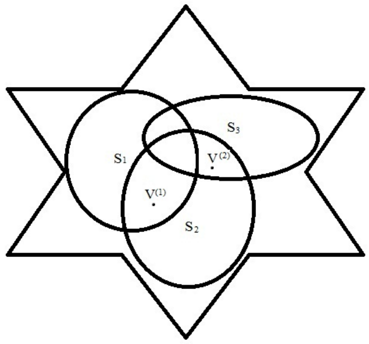

Fig. 1. The change of the convex subset with iterations.

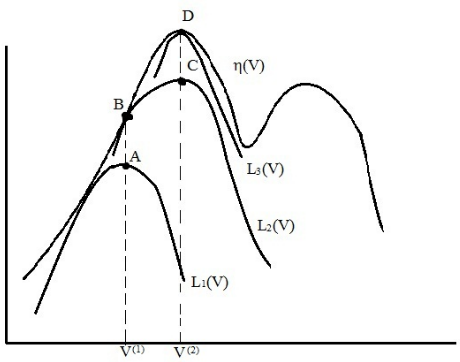

Fig. 2. The change of the quasi-concave lower bound with iterations.

IV. Simulation Results

In this section, we evaluate the performance of the proposed energy-efficient CoMP-CB. The simulation set-up is as follows. We consider a three-cell system, where each BS serves one user and the cell radius is 500 m. Each BS and each user are equipped with two antennas and each user has the same data rate requirement. The path loss follows 3GPP channel model [16], and the small-scale channel is subject to Rayleigh fading. Unless otherwise specified, we set the noise variance $\sigma_{i_k}^2$ as -76 dBm corresponding to a 46 dBm transmit power of each BS and a 5 dB cell-edge signal-to-noise ratio (SNR) under the path loss model. All the simulation results are obtained by averaging over 100 channel realizations. The overall circuit power consumption of the three BSs is either set as 255 W or 0 W, and the power amplifier efficiency $1/\rho$= 0.311 [17].

We first evaluate the convergence of the proposed iterative algorithm. The simulation result shows that the algorithm converges in 5 to 10 iterations under different data rate requirements. Due to the lack of space, we do not provide the figure here. The following results are all obtained after the iterative algorithm converges.

In Fig. 3 and Fig. 4, we show the average EE achieved by the proposed algorithm (with legend "max EE") versus the required data rate of each user with and without considering the circuit power consumption. For comparison, we provide the average EE of a scheme with legend "min Power", which is the CoMP-CB minimizing the overall transmit power under the

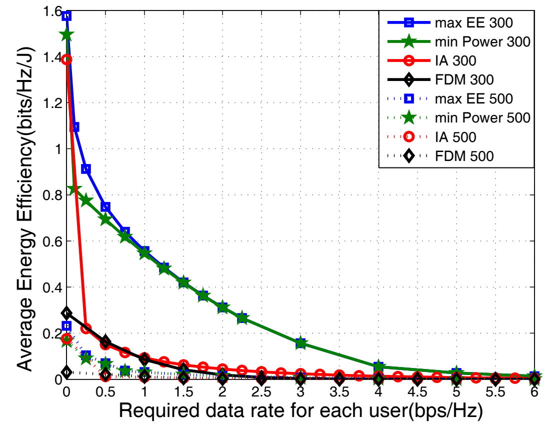

Fig. 3. Average EE versus data rate requirement, $P_c = 0$.

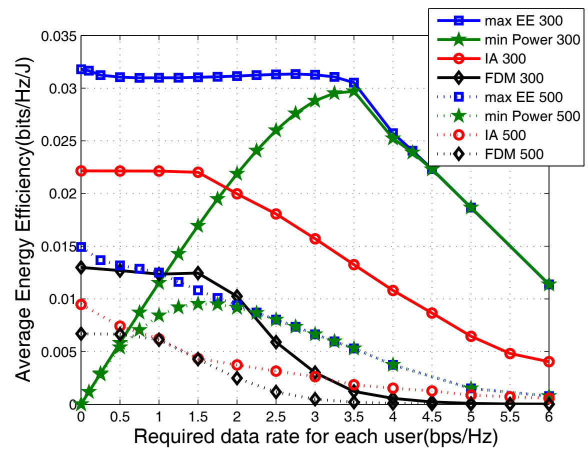

Fig. 4. Average EE versus data rate requirement, $P_c = 255$ W.

constraint of (5b) [2]. We consider the case of $P_c = 0$ to show the impact of the difference in objective functions: maximizing the EE and minimizing the transmit power. The distance between each BS and its serving user, d, is respectively set to be 300 m and 500 m. To demonstrate the impact of the QoS requirement, the value of r_{i_k} is set from zero (corresponding to the best effort traffic) to high values. As a result, the maximal transmit power in these two figures may far exceed 46 dBm to support the required data rate under the given system setting.

When P_c is set to be 0, the performance of the proposed EE-maximized precoder and the transmit power-minimized precoder in [2] becomes identical when the data rate requirement grows. However, when the value of r_{i_k} is very low, the proposed precoder achieves much higher EE than that in [2], especially when the user is closer to its master BS. When the practical value of P_c is taken into account, the performance gain of the proposed precoder is more obvious in a much wider region of the data rate requirement, because it transmits with higher data rate than the required value of r_{i_k} to maximize the EE. Toward the goal of minimizing the transmit power, the precoder in [2] transmits with the data rate of r_{i_k}, which yields a lower EE. When the data rate requirement is very high, the two precoders perform closely because the transmit power becomes dominant.

To show the individual contributions of the beamformer and power allocation, we also show the performance of the energy-efficient IA precoder $\mathbf{V}_{i_k}^{IA}$ in (18) and a frequency-division multiplexing (FDM) scheme where each BS uses 1/3 of the overall bandwidth for transmission and the transmit power allocated to each user is optimized to maximize the EE under the individual data rate constraints. It is shown that the IA precoder is more energy-efficient than the FDM scheme because of the multiplexing gain (i.e., high SE). However, both of them are inferior to the proposed precoder because they only optimize the power allocation while the proposed scheme jointly optimizes the beamformer and power allocation.

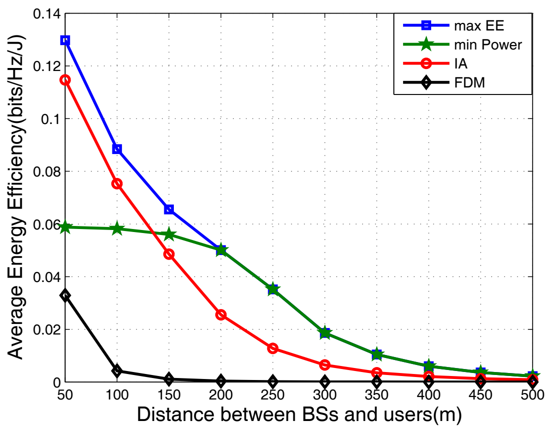

Fig. 5. Average EE versus user location, $P_c = 255$ W, $r_{i_k} = 5$ bps/Hz, cell-edge SNR is 5 dB.

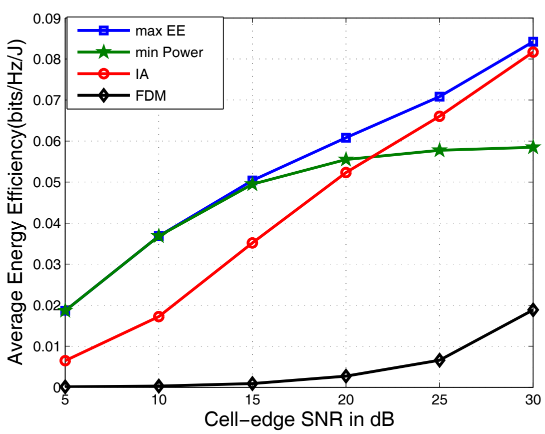

Fig. 6. Average EE versus cell-edge SNR, $P_c = 255$ W, $r_{i_k} = 5$ bps/Hz, d = 300 m.

In Fig. 5 and Fig. 6, we show the EE achieved by the four schemes versus the user location and cell-edge SNR. We can see that the "min Power" precoder is inferior to the proposed "max EE" precoder when the circuit power consumption dominates, i.e., when the users are located in cell-center and the cell-edge SNR is high. The proposed precoder is superior to the IA precoder, where the EE gain comes from providing a trade-off between the ICI and noise.

V. Conclusion

We studied energy-efficient precoder that maximizes the EE of CoMP-CB systems under the constraints of the minimal data rate requirement of each user. To find a solution of the non-convex optimization problem, we constructed a convex subset of the original constraint set and a quasi-concave lower bound of the EE. An iterative algorithm was proposed to maximize the lower bound of the EE within the convex subset. Simulation results showed that the proposed precoder achieves much higher EE than the transmit power minimization coordinated precoder when the circuit power consumption is dominant, and always outperforms the energy-efficient IA and FDM schemes.

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