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Energy-Efficient Coordinated Beamforming with Rate Dependent Processing Power

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***Abstract*—This paper studies energy-efficient coordinated beamforming in multi-cell multi-user multiple-input single-output (MISO) system. On contrary to the existing approaches where the power consumption of a base station is modeled as a convex or linear function, we consider a more practical model where part of the processing power depends on the rate provided by the base stations. Two optimization criteria are considered, namely network energy efficiency maximization and weighted sum energy efficiency maximization. We develop successive convex approximation based algorithms to tackle these difficult nonconvex problems. The numerical results illustrate that the rate dependent power consumption has a large impact on the energy efficiency, and, thus, has to be taken into account when devising energy-efficient transmission strategies.**

***Index Terms*—Energy efficiency, sequential convex approximation, circuit power, fractional programming, multi-cell.**

I. Introduction

To enable nearby cells to use the same transmission resources, interference coordination techniques have been of huge interest in last decades. Among those, a powerful method adopted in the current LTE-A systems is called *coordinated beamforming*, where base stations (BSs) can jointly design their beamforming vectors without sharing their data [1]. Coordinated beamforming has been widely studied for, e.g., sum rate maximization [2]–[4], and transmit power minimization [5], [6]. To aim at energy savings for future networks, energy efficiency has become an increasingly important design criterion [7]–[9]. For energy-efficient transmission, dealing with the power consumption caused by an increased number of BSs in coordinated beamforming plays a key role.

The energy efficiency maximization (EEmax) problems belong to the class of fractional programs, which have been widely studied in both single-cell [8] and multi-cell system models [9]–[11]. Nguyen *et al.* [9] considered the problem of maximizing the minimum EE among base stations to maintain EE fairness in a multi-cell multiuser multiple-input single-output (MISO) system. Coordinated beamforming for network EEmax in multi-cell multi-antenna systems was studied in [10], [11] where the latter incorporated the data rate constraints of the users in the optimization. To satisfy the heterogeneous energy efficiency requirements of different cells, the works in [12] and [13] proposed to use the weighted sum energy efficiency (WsumEE) as a performance measure. However, all these works only consider the circuit power as constant and do not account for the fact that a significant part of the power consumption depends on the data rate.

The rate dependent power has been assumed to be either linear or convex function of the data rate [14]–[16]. The linear case with uniform user rates in a single-cell system was investigated in [14] where zero-forcing beamforming with massive multiple-input-multiple-output (MIMO) setup was shown to achieve maximal EE. However, in a multi-cell network where the inter-cell interference becomes significant, zero-forcing method is highly suboptimal, because the degrees of freedom are used up for nulling both intra- and inter-cell interference. Furthermore, to completely eliminate the interference, the number of antennas at each BS should be equal to or larger than to the total number of users in the network. A general convex power consumption model in point-to-point MIMO orthogonal frequency-division multiplexing systems was considered in [15], [16].

In this paper, we study energy-efficient coordinated beamforming in multi-cell multi-user MISO systems with rate dependent power consumption. This is different from the related literature which adopts either a simple (i.e. rate-independent) power consumption model [11]–[13] or a simplified beamforming technique (i.e. zero-forcing) [14]. We extend the general rate dependent power consumption model from [15], [16] to account for the multi-user transmission. Two different optimization criteria are considered. The first one is the network EEmax which gives the maximum energy efficiency achieved in the network. The second one, on the other hand, is the weighted sum EEmax (WsumEEmax), which maximizes the sum of energy efficiencies of the cells. The latter is very relevant in the sense that it can satisfy heterogeneous energy efficiency requirements of different BS types and can be implemented in a decentralized manner [13].

II. System Model and Problem Formulation

A. System Model

We consider the downlink of a multi-cell MISO system with B cells. Each base station $b \in \mathcal{B} = \{1, \ldots, B\}$ equipped with N_b antennas transmits data to a group of K_b single-antenna users in its cell, represented by the set $\mathcal{K}_b$. Each user $k \in \mathcal{K} \triangleq \cup_{b\in\mathcal{B}}\mathcal{K}_b$ in the network is served only by a single BS which

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is denoted by $b_k \in \mathcal{B}$, i.e., $\mathcal{K}_b \cap \mathcal{K}_{b'} = \emptyset \; \forall b \neq b'$. The channel vector from BS b to user k is represented by $\mathbf{h}_{b,k} \in \mathbb{C}^{1\times N_b}$

In the downlink, data symbol s_k for user k is multiplied with the beamformer $\mathbf{w}_k \in \mathbb{C}^{N_b\times 1}$ before transmission. Accordingly, the received signal at user k is given by

$$y_k = \mathbf{h}_{b_k,k}\mathbf{w}_k s_k + \sum\nolimits_{j\in\mathcal{K}\setminus\{k\}} \mathbf{h}_{b_j,k}\mathbf{w}_j s_j + n_k \quad (1)$$

where $n_k \sim \mathcal{CN}(0,\sigma^2)$ is the background noise. The data streams are assumed to be independent, zero mean and unit power. It is also assumed that the BSs and users have perfect channel information. The data rate of user k is given by

$$R_k(\mathbf{w}) = W\log(1+\Gamma_k(\mathbf{w})) \quad (2)$$

where W is the bandwidth, $\mathbf{w} \triangleq \{\mathbf{w}_k\}_{k\in\mathcal{K}}$, and

$$\Gamma_k(\mathbf{w}) \triangleq \frac{|\mathbf{h}_{b_k,k}\mathbf{w}_k|^2}{N_0 + \sum_{j\in\mathcal{K}\setminus\{k\}} |\mathbf{h}_{b_j,k}\mathbf{w}_j|^2} \quad (3)$$

with $N_0 = \sigma^2 W$ is the SINR at user k.

B. Power Consumption Model

We combine the power consumption models from [14]–[16] and extend the general rate dependent power consumption model to account for the multi-user transmission. As a results, the total power consumption of cell b is modeled as

$$P_{\text{tot},b} = \frac{1}{\eta}\sum\nolimits_{k\in\mathcal{K}_b} ||\mathbf{w}_k||_2^2 + P_{\text{CP},b} + P_{\text{RD}}\delta(r_b) \quad (4)$$

where the first term is the data transmit power in the downlink, $\eta \in [0,1]$ is the power amplifier efficiency at the BS, $P_{\text{CP},b}$ is the rate independent total circuit power consumption, $P_{\text{RD}} \geq 0$ is a constant accounting for the coding, decoding and backhaul power consumption, and $\delta(r_b)$ is a differentiable, strictly increasing and convex function of the total sum rate r_b of BS b, satisfying $\delta(0) = 0$. $P_{\text{CP},b}$ in (4) is decomposed as

$$P_{\text{CP},b} = P_{\text{FIX}} + P_{\text{TC},b} \quad (5)$$

where P_{FIX} is a fixed power consumption required for site-cooling, control signaling, and the load-independent power of backhaul infrastructure and baseband processors, $P_{\text{TC},b}$ is the power consumption of the transceiver chains in cell b.[1] $P_{\text{TC},b}$ can be further decomposed as

$$P_{\text{TC},b} = N_b P_{\text{BS}} + P_{\text{SYN}} + K_b P_{\text{UE}} \quad (6)$$

where P_{BS} is the power per RF chain at each antenna, P_{SYN} is the power consumed by local oscillator and P_{UE} is the fixed circuit power of each user.

C. Problem Formulation

The problem of network EEmax with BS-specific power constraints can be expressed as

$$\max_{\{\mathbf{w}_k\}_{k\in\mathcal{K}}} \quad \frac{\sum_{b\in\mathcal{B}} \tilde{R}_b(\mathbf{w})}{g(\mathbf{w}) + P_{\text{RD}}\sum_{b\in\mathcal{B}}\delta(\tilde{R}_b(\mathbf{w}))} \quad (7a)$$

$$\text{s.t.} \quad \sum\nolimits_{k\in\mathcal{K}_b} ||\mathbf{w}_k||_2^2 \leq P_b, \; \forall b \in \mathcal{B} \quad (7b)$$

[1]All the fixed power values can be different for different BSs, but for simplicity, they are assumed to be equal. The rate dependent power consumption of BS b could be also modeled as $\sum_{k\in\mathcal{K}_b} P_{\text{RD}}\delta(r_k)$, where $\delta(r_k)$ is a function of individual user rate r_k. The algorithms presented in this paper can be straightforwardly applied to this model also.

where $g(\mathbf{w}) \triangleq \frac{1}{\eta}\sum_{k\in\mathcal{K}} ||\mathbf{w}_k||_2^2 + \sum_{b\in\mathcal{B}} P_{\text{CP},b}$ includes the power consumption which does not depend on the rate function, and $\tilde{R}_b(\mathbf{w})$ is a function denoting the total sum rate of BS b. Conventionally, the denominator of the objective function has been either linear or convex function of the power values [14]–[16]. However, as we can see, the rate dependent circuit power causes further complications, making also the total power consumption to be a nonconvex function.

The problem of WsumEEmax can be written as

$$\max_{\{\mathbf{w}_k\}_{k\in\mathcal{K}}} \quad \sum\nolimits_{b\in\mathcal{B}} \omega_b \frac{\tilde{R}_b(\mathbf{w})}{g_b(\tilde{\mathbf{w}}_b) + P_{\text{RD}}\delta(\tilde{R}_b(\mathbf{w}))} \quad (8a)$$

$$\text{s.t.} \quad \sum\nolimits_{k\in\mathcal{K}_b} ||\mathbf{w}_k||_2^2 \leq P_b, \; \forall b \in \mathcal{B} \quad (8b)$$

where $\tilde{\mathbf{w}}_b = \{\mathbf{w}_k\}_{k\in\mathcal{K}_b}$, $g_b(\tilde{\mathbf{w}}_b) \triangleq \frac{1}{\eta}\sum_{k\in\mathcal{K}_b} ||\mathbf{w}_k||_2^2 + P_{\text{CP},b}$ includes the power consumption which does not depend on the rate function, and ω_b is the energy efficiency priority weight factor for BS b. Despite the apparent similarity, the WsumEEmax problem is harder to solve compared to (7), simply because the objective (8a) is a sum of fractional functions, which is not quasiconcave even if the numerators and denominators are linear.

III. Proposed Solutions

A. Network Energy Efficiency Maximization

We remark that the problem (7) is not a concave fractional program for which efficient methods exist [17], [18]. The reason is that both the numerator and the denominator in (7a) are nonconvex functions. To find a more tractable reformulation, we introduce the following equivalent transformation of (7)

$$\max_{\{\mathbf{w}_k\}_{k\in\mathcal{K}},\{r_b\}_{b\in\mathcal{B}}} \quad \frac{\sum_{b\in\mathcal{B}} r_b}{g(\mathbf{w}) + P_{\text{RD}}\sum_{b\in\mathcal{B}}\delta(r_b)} \quad (9a)$$

$$\text{s.t.} \quad r_b \leq \sum\nolimits_{k\in\mathcal{K}_b} \log(1+\Gamma_k(\mathbf{w})), \forall b \in \mathcal{B} \quad (9b)$$

$$\sum\nolimits_{k\in\mathcal{K}_b} ||\mathbf{w}_k||_2^2 \leq P_b, \; \forall b \in \mathcal{B} \quad (9c)$$

where (7) and (9) are equivalent because the constraints in (9b) are active at optimality, and $\{r_b\}_{b\in\mathcal{B}}$ are new variables representing the total sum rate of each base station b. At this point, we note that the objective function is a linear-convex fractional function and the difficulty now is in the constraint (9b). To this end, by introducing new variables $\{\gamma_k\}_{k\in\mathcal{K}}$ representing the SINR of user k, the problem in (9) can be equivalently formulated as

$$\max_{\{\mathbf{w}_k,\gamma_k\}_{k\in\mathcal{K}},\{r_b\}_{b\in\mathcal{B}}} \quad \frac{\sum_{b\in\mathcal{B}} r_b}{g(\mathbf{w}) + P_{\text{RD}}\sum_{b\in\mathcal{B}}\delta(r_b)} \quad (10a)$$

$$\text{s.t.} \quad r_b \leq \sum\nolimits_{k\in\mathcal{K}_b} \log(1+\gamma_k), \forall b \in \mathcal{B} \quad (10b)$$

$$\gamma_k \leq \frac{|\mathbf{h}_{b_k,k}\mathbf{w}_k|^2}{N_0 + \sum_{j\in\mathcal{K}\setminus\{k\}} |\mathbf{h}_{b_j,k}\mathbf{w}_j|^2}, \forall k \in \mathcal{K} \quad (10c)$$

$$\sum\nolimits_{k\in\mathcal{K}_b} ||\mathbf{w}_k||_2^2 \leq P_b, \; \forall b \in \mathcal{B} \quad (10d)$$

where SINR constraints in (10c) are still nonconvex. By introducing a new variable β_k for total interference-plus-noise of user k [19], [4], we can further rewrite (10)

$$\max_{\{\mathbf{w}_k,\gamma_k,\beta_k\}_{k\in\mathcal{K}},\{r_b\}_{b\in\mathcal{B}}} \quad \frac{\sum_{b\in\mathcal{B}} r_b}{g(\mathbf{w}) + P_{\text{RD}}\sum_{b\in\mathcal{B}}\delta(r_b)} \tag{11a}$$

$$\text{s.t.} \quad \gamma_k \le |\mathbf{h}_{b_k,k}\mathbf{w}_k|^2/\beta_k, \forall k\in\mathcal{K} \tag{11b}$$

$$r_b \le \sum\nolimits_{k\in\mathcal{K}_b}\log(1+\gamma_k), \forall b\in\mathcal{B} \tag{11c}$$

$$\beta_k \ge N_0 + \sum\nolimits_{j\in\mathcal{K}\setminus\{k\}} |\mathbf{h}_{b_j,k}\mathbf{w}_j|^2, \forall k\in\mathcal{K} \tag{11d}$$

$$\sum\nolimits_{k\in\mathcal{K}_b} ||\mathbf{w}_k||_2^2 \le P_b,\ \forall b\in\mathcal{B} \tag{11e}$$

In the above problem, all the constraints are convex except the one in (11b) but it is in a form that lends itself to the application of successive convex approximation framework. Specifically the right hand side of (11b) is called a quadratic-over-linear function which is jointly convex with respect to β_k and $\mathbf{w}_k$. Thus, we can use the first-order lower approximation for the right side of (11b) as [13]

$$\begin{aligned} |\mathbf{h}_{b_k,k}\mathbf{w}_k|^2/\beta_k \ge\ & 2\text{Re}((\mathbf{w}_k^{(n)})^H\mathbf{h}_{b_k,k}^H\mathbf{h}_{b_k,k}\mathbf{w}_k)/\beta_k^{(n)} \\ & -(|\mathbf{h}_{b_k,k}\mathbf{w}_k^{(n)}|/\beta_k^{(n)})^2\beta_k \triangleq \Psi_k^{(n)}(\mathbf{w}_k,\beta_k). \end{aligned} \tag{12}$$

According to SCA principle we will replace the right side of (11b) by a convex lower bound. From (12), the problem at iteration n of the proposed SCA-based algorithm can be expressed as

$$\max_{\{\mathbf{w}_k,\gamma_k,\beta_k\}_{k\in\mathcal{K}},\{r_b\}_{b\in\mathcal{B}}} \quad \frac{\sum_{b\in\mathcal{B}} r_b}{g(\mathbf{w}) + P_{\text{RD}}\sum_{b\in\mathcal{B}}\delta(r_b)} \tag{13a}$$

$$\text{s.t.} \quad \gamma_k \le \Psi_k^{(n)}(\mathbf{w}_k,\beta_k), \forall k\in\mathcal{K} \tag{13b}$$

$$r_b \le \sum\nolimits_{k\in\mathcal{K}_b}\log(1+\gamma_k), \forall b\in\mathcal{B} \tag{13c}$$

$$\beta_k \ge N_0 + \sum\nolimits_{j\in\mathcal{K}\setminus\{k\}} |\mathbf{h}_{b_j,k}\mathbf{w}_j|^2, \forall k\in\mathcal{K} \tag{13d}$$

$$\sum\nolimits_{k\in\mathcal{K}_b} ||\mathbf{w}_k||_2^2 \le P_b,\ \forall b\in\mathcal{B} \tag{13e}$$

which is a concave-convex fractional program. The concave-convex fractional program can be transformed to an equivalent convex program with the Charnes-Cooper transformations [18] as $\bar{\mathbf{w}}_k = \phi\mathbf{w}_k, \bar{\gamma}_k = \phi\gamma_k, \bar{\beta}_k = \phi\beta_k, \bar{r}_b = \phi r_b$ and $\phi = 1/(\frac{1}{\epsilon}\sum_{k\in\mathcal{K}}||\mathbf{w}_k||_2^2 + \sum_{b\in\mathcal{B}}(P_{\text{RD}}\delta(r_b) + P_{\text{CP},b}))$. This yields

$$\max_{\{\bar{\mathbf{w}}_k,\bar{\gamma}_k,\bar{\beta}_k\}_{k\in\mathcal{K}},\{\bar{r}_b\}_{b\in\mathcal{B}}} \quad \sum\nolimits_{b\in\mathcal{B}} \bar{r}_b \tag{14a}$$

$$\text{s.t.} \quad \bar{\gamma}_k - \Psi_k^{(n)}(\bar{\mathbf{w}}_k,\bar{\beta}_k)) \le 0, \forall k\in\mathcal{K} \tag{14b}$$

$$\bar{r}_b - \sum\nolimits_{k\in\mathcal{K}_b}\phi\log(1+\tfrac{\bar{\gamma}_k}{\phi}) \le 0, \forall b\in\mathcal{B} \tag{14c}$$

$$\phi N_0 + \sum\nolimits_{j\in\mathcal{K}\setminus\{k\}} \tfrac{|\mathbf{h}_{b_j,k}\bar{\mathbf{w}}_j|^2}{\phi} - \bar{\beta}_k \le 0, \forall k\in\mathcal{K} \tag{14d}$$

$$\frac{1}{\epsilon}\sum\nolimits_{k\in\mathcal{K}} \tfrac{||\bar{\mathbf{w}}_k||_2^2}{\phi} + \sum\nolimits_{b\in\mathcal{B}}(P_{\text{RD}}\phi\delta(\tfrac{\bar{r}_b}{\phi}) + \phi P_{\text{CP},b}) \le 1 \tag{14e}$$

$$\sum\nolimits_{k\in\mathcal{K}_b} \tfrac{||\bar{\mathbf{w}}_k||_2^2}{\phi} \le \phi P_b. \tag{14f}$$

The optimal solutions for the original problem can be extracted as $\mathbf{w}_k^* = \bar{\mathbf{w}}_k^*/\phi^*, \gamma_k^* = \bar{\gamma}_k^*/\phi^*, \beta_k^* = \bar{\beta}_k^*/\phi^*, r_b^* = \bar{r}_b^*/\phi^*$. Thus, in the algorithm, we iteratively approximate (7) by (14) at iteration n of the SCA method until convergence. The procedure is presented in Algorithm 1. The convergence of the objective function for Algorithm 1 can be proved following the same steps as in [20] and is, thus, omitted here for brevity.

Algorithm 1 Proposed SCA-based beamformer design for the network energy efficiency maximization problem.

Initialization: Set $n = 0$, generate initial points $(\mathbf{w}_k^{(n)}, \beta_k^{(n)}), \forall k\in\mathcal{K}$.

repeat
- Solve (14) with $(\mathbf{w}_k^{(n)}, \beta_k^{(n)}), \forall k\in\mathcal{K}$ and denote optimal values as $(\bar{\mathbf{w}}_k^*, \bar{\beta}_k^*), \forall k\in\mathcal{K}$. Set $n := n+1$.
- Update $(\mathbf{w}_k^{(n)} = \bar{\mathbf{w}}_k^*, \beta_k^{(n)} = \bar{\beta}_k^*)$.

until convergence

Output: $\mathbf{w}_k^* = \frac{\bar{\mathbf{w}}_k^*}{\phi^*}, \forall k\in\mathcal{K}$

Note that the algorithm applies to any convex function $\delta(\cdot)$.

Remark 1. If the power consumption has a linear dependence on the rate, i.e., $\delta(r_b) = r_b$ and P_{RD} is the same for all the BSs, $P_{\text{RD}}\delta(r_b)$ does not affect on the optimal variables of (7). In this special case, (7a) is equal to $\min(g(\mathbf{w})/\sum_{b\in\mathcal{B}}\tilde{R}_b(\mathbf{w}) + P_{\text{RD}})$. As can be seen, P_{RD} becomes a constant in the objective function and could be ignored in the optimization process (but not in the actual utility).

B. Weighted Sum Energy Efficiency Maximization

Here we again apply SCA framework to solve (8). As a first step we write the following equivalent transformation of (8)

$$\max_{\{t_b\}_{b\in\mathcal{B}},\{\mathbf{w}_k\}_{k\in\mathcal{K}}} \quad \sum\nolimits_{b\in\mathcal{B}}\omega_b t_b \tag{15a}$$

$$\text{s.t.} \quad t_b \le \frac{\tilde{R}_b(\mathbf{w})}{g_b(\tilde{\mathbf{w}}_b) + P_{\text{RD}}\delta(\tilde{R}_b(\mathbf{w}))}, \forall b\in\mathcal{B} \tag{15b}$$

$$\sum\nolimits_{k\in\mathcal{K}_b} ||\mathbf{w}_k||_2^2 \le P_b,\ \forall b\in\mathcal{B} \tag{15c}$$

which is in fact an epigraph form of (8). Next, we can further equivalently reformulate (15) as

$$\max_{\{t_b,r_b\}_{b\in\mathcal{B}},\{\mathbf{w}_k,\gamma_k\}_{k\in\mathcal{K}}} \quad \sum\nolimits_{b\in\mathcal{B}}\omega_b t_b \tag{16a}$$

$$\text{s.t.} \quad t_b \le \frac{r_b^2}{g_b(\tilde{\mathbf{w}}_b) + P_{\text{RD}}\delta(r_b)}, \forall b\in\mathcal{B} \tag{16b}$$

$$\gamma_k \le \Gamma_k(\mathbf{w}), \forall k\in\mathcal{K} \tag{16c}$$

$$\sum\nolimits_{k\in\mathcal{K}_b}\log(1+\gamma_k) \ge r_b^2, \forall b\in\mathcal{B} \tag{16d}$$

$$\sum\nolimits_{k\in\mathcal{K}_b} ||\mathbf{w}_k||_2^2 \le P_b,\ \forall b\in\mathcal{B}. \tag{16e}$$

We have used r_b^2 in (16d) rather than r_b as in (13c). The reason is that we want (16b) to be in a similar form to (11b) so that application of SCA method becomes easier as shown shortly. The equivalence between (16) and (15) is guaranteed since all the constraints (16b)-(16d) are active at optimality. The constraints in (16c) are equivalent to (10c) and can be handled as shown in (11) and (12). To find a tractable reformulation of the nonconvex constraints (16b), we can equivalently split it into the following two constraints

$$t_b \le \frac{r_b^2}{z_b}, \forall b\in\mathcal{B} \tag{17a}$$

$$z_b \ge g_b(\tilde{\mathbf{w}}_b) + P_{\text{RD}}\delta(R_b(\mathbf{w})), \forall b\in\mathcal{B}, \tag{17b}$$

where we have introduced new variables $\{z_b\}_{b\in\mathcal{B}}$. Now, (17b) is convex and (17a) is in the same form as (11b). Following the same way to deal with (11b), we can use the first-order lower approximation for the right side of (17a) as

$$\frac{r_b^2}{z_b} \geq \frac{2r_b^{(n)}}{z_b^{(n)}} r_b - (\frac{r_b^{(n)}}{z_b^{(n)}})^2 z_b \triangleq \phi_b^{(n)}(r_b, z_b). \tag{18}$$

By using the linear approximations in (12) and (18), we can use SCA where the problem to be solved at iteration n becomes

$$\max_{\{t_b, r_b, z_b\}_{b\in\mathcal{B}}, \{\mathbf{w}_k, \gamma_k, \beta_k\}_{k\in\mathcal{K}}} \sum\nolimits_{b\in\mathcal{B}} \omega_b t_b \tag{19a}$$

$$\text{s.t.} \quad t_b \leq \phi_b^{(n)}(r_b, z_b), \forall b \in \mathcal{B} \tag{19b}$$

$$\gamma_k \leq \Psi_k^{(n)}(\mathbf{w}_k, \beta_k), \forall k \in \mathcal{K} \tag{19c}$$

$$(8b), (16d), (17b), (11d) \tag{19d}$$

The algorithm for WsumEEmax problem is called **Algorithm 2** in the numerical results. Similar to Algorithm 1, the convergence of the objective function for Algorithm 2 can be proved following the same steps as in [20].

IV. Numerical Results

We evaluate the performance by assuming quasistatic frequency flat Rayleigh fading channels and considering 7-cell wrap-around model, where each user suffers interference from six neighboring base stations. We assume a small-cell setup where the inter-BS distance d_{B} is 120 m. The radius of each cell is assumed to be $\frac{d_{\text{B}}}{2}$, i.e., the cell edges are overlapping and the users are randomly dropped to the cell edges. The path loss in dB is modeled as 35 + 30$\log(d)$ with distance d in meters and the shadowing as log-normal distribution with a standard deviation of 8 dB. The algorithms are stopped when the change over last five iterations is smaller than $\xi = 10^{-4}$. We set $\delta(r_b) = r_b^m$, where $m \geq 1$ is any rational number, $\omega_b = 1$ and $K_b = K, N_b = N, \forall b \in \mathcal{B}$, and the other simulation parameters are adopted from [21], [14], [15], [16] as: $W = 20$ MHz, $P_{\text{FIX}} = 3$ Watts, $P_{\text{BS}} = 0.4$ Watts, $P_{\text{SYN}} = 1$ Watt, $P_{\text{UE}} = 0.1$ Watts, $P_b = 21$ dBm, $\eta = 0.2, N_0 =$ -98 dBm.

Fig. 1 illustrates the average energy efficiency versus P_{RD} for different values of exponent m. We compare the proposed algorithm with the conventional method where the rate dependent power consumption is not taken into account in the optimization problem but the results in Fig. 1 include also the impact of rate dependent power (Alg. 1, $P_{\text{RD}} = 0$). As observed mathematically in Remark 1, the rate dependent term does not affect the optimal solution of network EE when $m = 1$. However, for a general model ($m > 1$), there is a sharp difference which shows the importance of including the rate dependent power consumption in the beamformer optimization. Note that the gains of Alg. 1 depend on the setup. Larger gains can be achieved in the systems with low transmit power devices, where the rate dependent signal processing power consumption is significant part of the total power consumption. Fig. 1 also reveals that the power model has a huge impact on the energy efficiency which shows the importance of accurate power modeling.

Fig. 2 compares the weighted sum energy efficiency performance with different exponent values m for the same simulation parameters as those in Fig. 1. Here, we similarly compare Alg. 2 with the one where the rate dependent power consumption is not taken into account in the optimization problem (Alg. 2, $P_{\text{RD}} = 0$). We can see that for the WsumEEmax, Alg. 2 offers significant performance improvement compared to conventional method even when linear rate dependent power consumption model is used (i.e., $m = 1$).

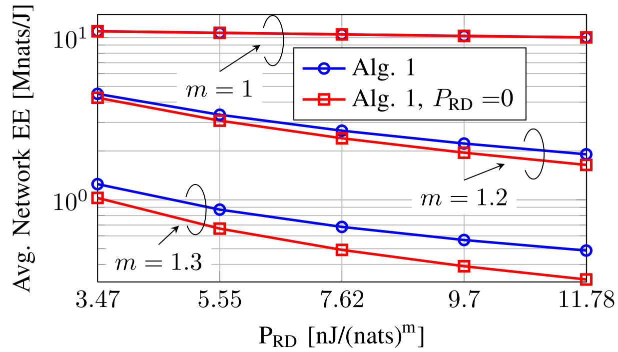

Fig. 1. Energy efficiency comparison of the algorithms for different rate dependent power consumption models with $N = 4$, $K = 2$.

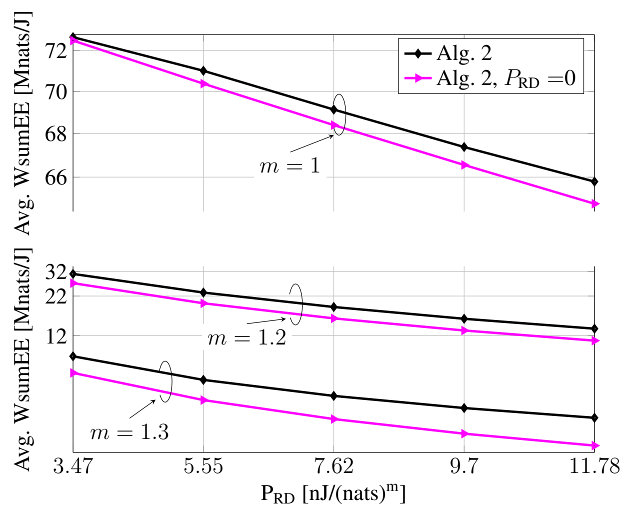

Fig. 2. Weighted sum energy efficiency comparison of the algorithms for different rate dependent power consumption models with $N = 4$, $K = 2$.

Fig. 3 plots the convergence of Algs. 1 and 2. We can see that both algorithms converge relatively fast in the considered setting and the obtained solution is insensitive to initial points. We have numerically observed that the proposed algorithms can return a high-quality solution (i.e., close to the convergence point) after around 10 iterations. The convergence speed could be further increased by choosing a more appropriate initial point which is left for future work.

Finally, Fig. 4 shows the average energy efficiency for the different numbers of transmit antennas N. Note that in this figure, the actual network energy efficiency is also shown for Alg. 2. We can see that there is only a minor performance gap between Algs. 1 and 2, which is due to the fact $w_b = 1, \forall b$. The fairness and EE can be further controlled by adjusting the priority weights. We also compare Algs. 1 and 2 with the uncoordinated method, where each base station tries to

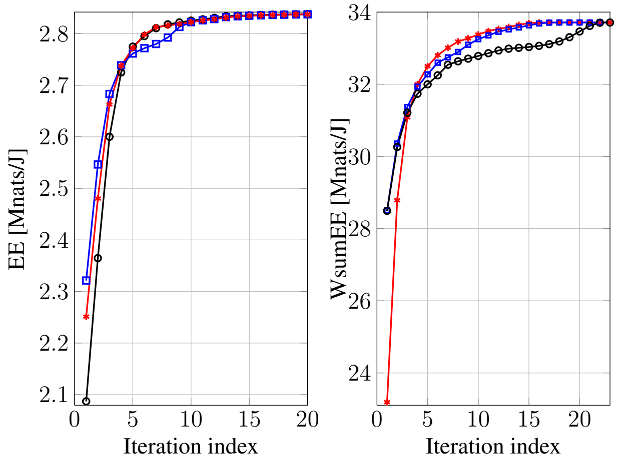

Fig. 3. Convergence illustration of Alg. 1 (left) and Alg. 2 (right) for three initial points with $N = 4$, $K = 2$, $m = 1.2$, $P_{\text{RD}} = 3.47 \times 10^{-9}$.

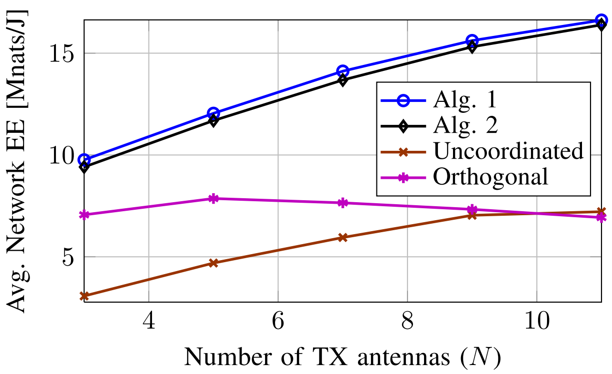

Fig. 4. Average energy efficiency vs. number of TX antennas N with $K = 3, P_{\text{RD}} = 3.47 \times 10^{-9}, m = 1$.

maximize its own energy efficiency without any coordination, and the orthogonal access method, where the bandwidth is divided into 7 orthogonal sub-bands so that each BS occupies $W/7$ bandwidth. As seen in Fig. 4, huge performance gains can be achieved using coordinated beamforming.

V. Conclusions

This paper has studied multi-cell energy-efficient coordinated beamforming with rate dependent power consumption model. We have considered two different optimization criteria: network energy efficiency maximization and weighted sum energy efficiency maximization. The framework for the proposed solutions has been based on successive convex approximation principle. The numerical results have illustrated that the rate dependent power consumption has a significant impact on the energy efficiency and thus has to be accounted for when devising energy-efficient transmission strategies.

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