Energy Efficient Clustering and Beamforming for Cooperative Multicell Networks

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Abstract. Network densification is the most important way to improve the network capacity and hence is widely adopted to handle the ever-increasing mobile traffic demand. However, network densification will make the inter-cell interference severe and also significantly increase the energy budget. Multicell cooperative transmission is an efficient way to mitigate the inter-cell interference and plays an important role in energy efficiency optimization. This paper investigates the energy efficient multi-cell cooperation strategy for dense wireless networks. Joint cluster forming and beamforming are considered to optimize the energy efficiency (evaluated by bits/Hz/J). The optimization problem is then decoupled into two subproblems, i.e., energy efficient beamforming problem and energy efficient cluster forming problem. The fractional programming and Lagrangian duality theory are used to obtain the optimal beamformer. Coalition formation game theory is exploited to solve the cluster forming problem. The proposed energy efficient clustering and beamforming strategy can provide flexible network service according to spatially uneven traffic and greatly improve the network energy efficiency.

Keywords: Cooperative transmission · Energy efficiency · Beamforming · Clustering · Coalition formation game

1 Introduction

Network densification has been historically adopted for network capacity improvement and it will be persist in the future to handle the increasingly growing wireless traffic [16,18]. However, the dense deployment of base station (BS) leads to the network energy consumption increase. As the greatly increased energy efficiency has been listed as one of the main objectives when designing 5G wireless network [1], it is necessary to design more energy efficient strategies. Multicell cooperative transmission (MCT) is an efficient technique in interference managements [13,17]. The researches in [12] show that when all the BSs are coordinated, the spectral efficiency scales linearly with the signal-to-noise ratio

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(SNR). The basic idea of MCT is to let multiple BSs cooperate and act as a single Multiple Input Multiple Output (MIMO) transceiver, hence some of the interference are turned into useful signals. Consequently, the network throughput is greatly improved. The MCT also plays a vital role in energy efficiency optimization. In [5], an energy efficiency analysis framework for MCT is proposed and the results show that when the backhauling and cooperative processing power are carefully controlled, MCT can be energy efficient, especially for cell-edge communication.

The two main problems for energy efficient MCT design are how to form clusters with desirable size, and how to efficiently obtain the multicell beamformers. The gains of MCT are saturated with the growing number of cooperating BSs due to the excessive overheads, e.g., complexity, channel estimation and increased power consumption [8]. Hence the cooperative clusters have to be carefully designed to obtain the optimal trade-off between the performance gain and associated overhead. In [3], a novel affinity propagation model is used to semi-dynamically form the cooperative cluster. The proposed algorithm can greatly improve network throughput with low complexity. Coalition formation game (CFG) studies the complex interactions among players and the formation of cooperating groups, referred to as coalitions [11]. Hence, CFG is well suited for the BSs clustering problem and have been studied in [15], where CFG is used to form the small cells cluster to optimize the trade-off between the benefits and costs associated with cooperation. On the other hand, energy efficient beamforming is also important for MCT. In [4], the downlink-uplink duality theory and geometric programming are used to find the beamformer that maximize the network energy efficiency (EE, defined as the sum throughput to power consumption). In [14], minimum mean square error (MMSE) based energy efficient beamforming strategy is proposed to maximize the worst-case EE. However, [4,14] only focus on the static cooperative cluster.

In this paper, we study the energy efficient clustering and beamforming problem for cooperative multicell networks. A energy efficiency optimization problem that jointly considers dynamic clustering and beamforming is formulated. Due to the combinatorial nature of the clustering and beamforming in cooperative multicell networks, the joint optimization problem is extremely hard to solve. To efficiently solve it, the problem is decoupled into two subproblem, i.e., the cluster forming problem and the energy efficient beamforming problem. The CFG and fractional program are used to solve them respectively. The remainder of this article is organized as follows. We first describe the system model in Sect. 2. Then the energy efficient clustering and beamforming problem is formulated and efficiently solved in Sect. 3. In Sect. 4, numerical results are presented. Finally, we conclude the article in Sect. 5.

2 System Model

2.1 Signal Model

We consider the downlink of a cooperative multicell network where a set $\mathcal{Q}$ of BSs, each equipped with M antennas, is serving a set $\mathcal{I}$ of user equipments (UEs) equipped with N antennas. Assume that the BSs are partitioned into several clusters and jointly serve UEs. Let $Q = (Q_1, \ldots, Q_k, \ldots, Q_K)$ denote a partition of $\mathcal{Q}$ and Q_k denotes the kth cooperative cluster. The set of serving UEs in cluster k is denoted as I_k. Let $\mathbf{H}_{i_k}^{q_l} \in \mathbb{C}^{N\times M}$ denote the channel between qth BS in cluster l and the ith user in the kth cluster. $\mathbf{H}_{i_k}^{l} \in \mathbb{C}^{N\times MQ_l}$ denotes the channel matrix between all BSs in cluster l to user i_k. Assume that each BS only transmit a single data stream to each UE and let $\mathbf{v}_{i_k}^{q_k} \in \mathbb{C}^{M\times 1}$ denote the beamformer from BSs q_k to UE i_k. Let $\mathbf{v}_{i_k} = \left[(\mathbf{v}_{i_k}^{1})^H, \ldots, (\mathbf{v}_{i_k}^{Q_k})^H\right]^H \in \mathbb{C}^{MQ_k\times 1}$ denote the beamformer collection intended for user i_k. Denote the transmitted signal for UE i_k as s_{i_k}, and then the received signal of user i_k can be expressed as

$$\mathbf{y}_{i_k} = \mathbf{H}_{i_k}^{k}\mathbf{v}_{i_k}s_{i_k} + \sum_{j_k\neq i_k}\mathbf{H}_{i_k}^{k}\mathbf{v}_{j_k}s_{j_k} + \sum_{l\neq k}\sum_{j_l\in I_l}\mathbf{H}_{i_k}^{l}\mathbf{v}_{j_l}s_{j_l} + \mathbf{z}_{i_k} \tag{1}$$

Let $\mathbf{u}_{i_k} \in \mathbb{C}^{N\times 1}$ denote the receiver beamformer to decode the intended signal. The estimated signal is $\hat{s}_{i_k} = \mathbf{u}_{i_k}^H\mathbf{y}_{i_k}$. Then the mean square error (MSE) of UE i_k can be calculated as

$$\begin{aligned} e_{i_k} &= \mathbb{E}_{s,\mathbf{z}}\left[(\hat{s}_{i_k} - s_{i_k})(\overline{\hat{s}_{i_k}} - \overline{s_{i_k}})\right] \\ &= (1 - \mathbf{u}_{i_k}^H\mathbf{H}_{i_k}^{k}\mathbf{v}_{i_k})(1 - \overline{\mathbf{u}_{i_k}^H\mathbf{H}_{i_k}^{k}\mathbf{v}_{i_k}}) + \sum_{(l,j)\neq(k,i)}\mathbf{u}_{i_k}^H\mathbf{H}_{i_k}^{l}\mathbf{v}_{j_l}\mathbf{v}_{j_l}^H(\mathbf{H}_{i_k}^{l})^H\mathbf{u}_{i_k} + \sigma^2\mathbf{u}_{i_k}^H\mathbf{u}_{i_k} \end{aligned} \tag{2}$$

The achievable rate of UE i_k can be expressed as

$$R_{i_k} = \log\left|\mathbf{I}_N + \mathbf{H}_{i_k}^{k}\mathbf{v}_{i_k}\mathbf{v}_{i_k}^H(\mathbf{H}_{i_k}^{k})^H\left(\sum_{(l,j)\neq(k,i)}\mathbf{H}_{i_k}^{l}\mathbf{v}_{j_l}\mathbf{v}_{j_l}^H(\mathbf{H}_{i_k}^{l})^H + \sigma^2\mathbf{I}_N\right)^{-1}\right| \tag{3}$$

2.2 Power Consumption Model

The power consumption at a certain BS q_k can be modeled as

$$P_{q_k} = \xi P_{q_k}^{tx} + P_{q_k}^{sp,ct} + P_{q_k}^{bh} \tag{4}$$

where $P_{q_k}^{tx}$, $P_{q_k}^{sp,ct}$ and $P_{q_k}^{bh}$ denote the transmission power, signal processing power consumption and backhaul power consumption respectively, ξ is the reciprocal of power amplifier efficiency. Define $\boldsymbol{\Phi}_{q_k}$ as the row selection matrix which has all zeros except M ones on the main diagonal corresponding to the M antennas of BS q_k. Then, the total transmission power can be expressed by

$$P_{q_k}^{tx} = \sum_{i_k \in \mathcal{I}_k} \mathbf{v}_{i_k}^H \boldsymbol{\Phi}_{q_k}^H \boldsymbol{\Phi}_{q_k} \mathbf{v}_{i_k} \tag{5}$$

The capacity gain brought by MCT is accompanied with the increased power consumption. MCT introduces additional operation on each BSs, the signal to be transmitted should be exchanged by BSs through the backhaul and the joint signal processing is needed to suit joint transmissions. Hence, we refer to the power consumption model in [9] and the signal processing power is modeled to be a quadratic function of the cooperative cluster size as follows

$$P_{q_k}^{sp,ct} = p_{q_k}^{sp}(0.87 + 0.1\,|Q_k| + 0.03\,|Q_k|^2) \tag{6}$$

The backhaul power consumption is caused by data exchange in the cluster and is modeled as

$$P_{q_k}^{bh} = \frac{1}{C_{bh}}(\frac{2pq\,|Q_k|^2}{T_s}) \tag{7}$$

where C_{bh} denotes the backhaul capacity and T_s denotes the symbol period. p and q represent the additional pilot density and relevant signaling, respectively.

3 Energy Efficient Clustering and Beamforming

3.1 Problem Formulation

For kth cluster, the throughput can be written as

$$C_k(\{\mathbf{v}_{i_k}\}) = \sum_{i_k \in I_k} R_{i_k} \tag{8}$$

The total power consumption of k-th cluster is given by

$$P_k(\{\mathbf{v}_{i_k}\}) = \sum_{q_k \in Q_k} P_{q_k} = \xi \sum_{i_k \in I_k} \mathbf{v}_{i_k}^H \mathbf{v}_{i_k} + P_c \tag{9}$$

where P_c is the total circuit power consumption. Energy efficiency (EE) of the whole network is defined as $\mathrm{EE}(\{\mathbf{v}_{i_k}\}, Q) = \frac{\sum_{k=1}^{K} C_k(\{\mathbf{v}_{i_k}\})}{\sum_{k=1}^{K} P_k(\{\mathbf{v}_{i_k}\})}$. Hence, the energy efficient clustering and beamforming problem can be formulated as

$$\begin{aligned} \mathbf{P1}: \quad & \max_{\{\mathbf{v}_{i_k}\}, Q} \quad \mathrm{EE}(\{\mathbf{v}_{i_k}\}, Q) \\ & \text{s.t.} \quad \sum_{i_k \in I_k} \mathbf{v}_{i_k}^H \boldsymbol{\Phi}_{q_k}^H \boldsymbol{\Phi}_{q_k} \mathbf{v}_{i_k} \le p_{q_k}, \ \forall q_k \in \mathcal{Q} \end{aligned} \tag{10}$$

The above problem is hard to solve, so we decouple the problem and use the hierarchical iterative algorithm to solve it. In outer iteration, the CFG is exploited to obtain the network partition Q. In inner iteration, the energy efficient beamforming problem is solved based on the given network partition Q.

3.2 Energy Efficient Beamforming

When the clusters are given, the origin problem can be rewritten as

$$\begin{aligned} \mathbf{P2}: \quad & \max_{\{\mathbf{v}_{i_k}\}} && \mathrm{EE}(\{\mathbf{v}_{i_k}\}, Q) \\ & \text{s.t.} && \sum_{i_k \in I_k} \mathbf{v}_{i_k}^H \boldsymbol{\Phi}_{q_k}^H \boldsymbol{\Phi}_{q_k} \mathbf{v}_{i_k} \le p_{q_k}, \ \forall q_k \in \mathcal{Q} \end{aligned} \tag{11}$$

Proposition 1. ***P2*** *has optimal objective value* θ^* *if and only if* $f(\theta^*) = 0$, *where univariate function* $f : \mathbb{R} \longmapsto \mathbb{R}$ *is defined as*

$$\begin{aligned} f(\theta) \triangleq \max_{\{\boldsymbol{v}_{i_k}\}} & \left\{ \sum_{k=1}^{K} C_k(\{\boldsymbol{v}_{i_k}\}) - \theta \sum_{k=1}^{K} P_k(\{\boldsymbol{v}_{i_k}\}) \right\} \\ \text{s.t.} & \sum_{i_k \in I_k} \boldsymbol{v}_{i_k}^H \boldsymbol{\Phi}_{q_k}^H \boldsymbol{\Phi}_{q_k} \boldsymbol{v}_{i_k} \le p_{q_k}, \ \forall q_k \in \mathcal{Q} \end{aligned} \tag{12}$$

Proof. Based on the analysis in [7], we can conclude that $f(\theta)$ is a monotonically decreasing function of θ and the equation $f(\theta) = 0$ has a unique solution θ^*. Therefore if we find certain θ that makes the objective function of (12) equals to zero, then the corresponding beamformers are also the optimal beamformers of problem **P2**.

Note that the problem in (12) is hard to solve due to the non-convexity of capacity $C_k(\{\mathbf{v}_{i_k}\})$, we introduce a set of new weight variables $\{w_{i_k}\}$ for each user. Then the problem can be reformulated as:

$$\begin{aligned} \mathbf{P3}: \quad & \max_{\{\mathbf{v}_{i_k}\},\{\mathbf{u}_{i_k}\},\{w_{i_k}\}} && \sum_{k} \sum_{i_k \in \mathcal{I}_k} \left(\log(w_{i_k}) - w_{i_k} e_{i_k}\right) - \theta \sum_{k} \left(\xi \sum_{i_k \in \mathcal{I}_k} \mathbf{v}_{i_k}^H \mathbf{v}_{i_k} + P_c \right) \\ & \text{s.t.} && \sum_{i_k \in \mathcal{I}_k} \mathbf{v}_{i_k}^H \boldsymbol{\Phi}_{q_k}^H \boldsymbol{\Phi}_{q_k} \mathbf{v}_{i_k} \le p_{q_k}, \ \forall q_k \in \mathcal{Q} \\ & && e_{i_k} \text{ is given by (2).} \end{aligned} \tag{13}$$

Similar to [6,10], we can conclude that if $(\{\mathbf{v}_{i_k}^*\}, \{\mathbf{u}_{i_k}^*\}, \{w_{i_k}^*\})$ is the optimal solution to **P2**, then $\{\mathbf{v}_{i_k}^*\}$ must be the optimal solution to **P1** and (12). Conversely if $\{\mathbf{v}_{i_k}^*\}$ is the optimal solution of **P2** and (12), then $(\{\mathbf{v}_{i_k}^*\}, \{\mathbf{u}_{i_k}^*\}, \{w_{i_k}^*\})$ must be the optimal solution to **P2**, where

$$\begin{aligned} \mathbf{u}_{i_k}^* &= \boldsymbol{\Sigma}_{i_k}^{-1}\left(\{\mathbf{v}_{i_k}^*\}\right) \mathbf{H}_{i_k}^k \mathbf{v}_{i_k}^* \\ w_{i_k}^* &= \left(1 - (\mathbf{v}_{i_k}^*)^H (\mathbf{H}_{i_k}^k)^H \boldsymbol{\Sigma}_{i_k}^{-1}\left(\{\mathbf{v}_{i_k}^*\}\right) \mathbf{H}_{i_k}^k \mathbf{v}_{i_k}^*\right)^{-1} \end{aligned} \tag{14}$$

with $\boldsymbol{\Sigma}_{i_k}\left(\{\mathbf{v}_{i_k}^*\}\right) = \sum_{(l,j)} \mathbf{H}_{i_k}^l \mathbf{v}_{jl} \mathbf{v}_{jl}^H (\mathbf{H}_{i_k}^l)^H + \sigma^2 \mathbf{I}$.

In what follows, we solve **P3** for given θ, $\{\mathbf{u}_{i_k}\}$ and $\{w_{i_k}\}$, which is a convex optimization problem. the Lagrangian function of **P3** can be stated as

$$\mathcal{L}(\{\mathbf{v}_{i_k}\},\{\lambda_{q_k}\}) = \sum_{k=1}^{K}\sum_{i_k\in I_k} w_{i_k}\left(1+\sum_{(l,j)}\mathbf{u}_{i_k}^H\mathbf{H}_{i_k}^l\mathbf{v}_{j_l}\mathbf{v}_{j_l}^H(\mathbf{H}_{i_k}^l)^H\mathbf{u}_{i_k}-\mathbf{u}_{i_k}^H\mathbf{H}_{i_k}^k\mathbf{v}_{i_k}-\mathbf{v}_{i_k}^H(\mathbf{H}_{i_k}^k)^H\mathbf{u}_{i_k}\right) + \theta\xi\sum_{k=1}^{K}\sum_{i_k\in I_k}\mathbf{v}_{i_k}^H\mathbf{v}_{i_k}+\sum_{q_k\in\mathcal{Q}}\lambda_{q_k}\left(\sum_{i_k\in I_k}\mathbf{v}_{i_k}^H\boldsymbol{\Phi}_{q_k}\mathbf{v}_{i_k}-p_{q_k}\right) \tag{15}$$

where $\{\lambda_{q_k}\}$ denote the Lagrange multipliers associated with the power constraints. Applying Lagrangian dual theory and the Karush-Kuhn-Tucker (KKT) conditions, the optimal beamformer is given by

$$\mathbf{v}_{i_k}^* = w_{i_k}\left(\sum_{(l,j)}(\mathbf{H}_{j_l}^k)^H\mathbf{u}_{j_l}\mathbf{u}_{j_l}^H\mathbf{H}_{j_l}^k+\theta\xi\mathbf{I}+\sum_{q_k\in\mathcal{Q}_k}\lambda_{q_k}\boldsymbol{\Phi}_{q_k}^H\boldsymbol{\Phi}_{q_k}\right)^{-1}(\mathbf{H}_{i_k}^k)^H\mathbf{u}_{i_k} \tag{16}$$

The optimal Lagrange multipliers $\{\lambda_{q_k}^*\}$ can be obtained by gradient method. Then we develop Algorithm 1 as below to numerically search the optimal value of θ and $\{\mathbf{v}_{i_k}\}$.

Algorithm 1. Energy efficient beamforming

1: Initialize θ^0
2: Initialize $\{\mathbf{v}_{i_k}^0\}$
3: **repeat**
4: Sequentially update $\mathbf{u}_{i_k}^t$ $w_{i_k}^t$
5: update $\mathbf{v}_{i_k}^{t+1}$ and θ^{t+1}
6: **until** certain stopping criteria met.

3.3 Energy Efficient Clustering as a Coalition Formation Game

We define the energy efficient cluster forming game (EECFG) as a triplet, $\mathbb{G}_{\text{EECF}} = (\mathcal{Q}, u, Q)$ in a characteristic form. The players, namely BSs, are affected each other through mutual interference, and they seek to form cooperative clusters to improve energy efficiency. Moreover, u is a characteristic function that quantifies the value of a coalition. $Q = (Q_1,\ldots,Q_k,\ldots,Q_K)$ which satisfies $\forall k_1,k_2\in\{1,\ldots,K\}, Q_{k_1}\cap Q_{k_2}=\varnothing, \bigcup_{k=1}^{K}Q_k=\mathcal{Q}$ is a partition of $\mathcal{Q}$ and shows a cooperative structure of the network. Coalition value set is defined as

$$u(Q_k) = \{\boldsymbol{\upsilon}(Q_k)\in\mathbb{R}^{|Q_k|}|\upsilon_b(Q_k),\forall b\in Q_k\} \tag{17}$$

where $\upsilon_{q_k}(Q_k)$ is an element of $\boldsymbol{\upsilon}(Q_k)$ and represents the utility that player $q_k\in Q_k$ can obtain in the coalition Q_k. Here, we define the BS' utility as the EE it achieves when serving attached users. Note that the utility obtained by each BS in Q_k depends on the joint strategies that all BSs in Q_k select and the coalition value cannot be arbitrarily apportioned among the members. Hence, the proposed $\mathbb{G}_{\text{EECF}}$ has a nontransferable utility (NTU). Therefore, we adopt merge and split rules to obtain the optimal solution of $\mathbb{G}_{\text{EECF}}$. The modified merge and split rules are defined as follows

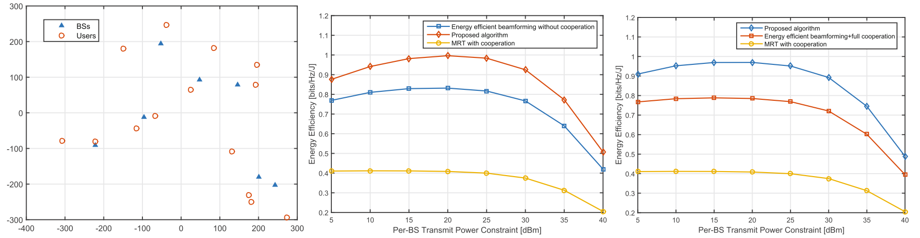
Definition 1. *Merge rule: merge any two coalitions* Q_{k_1},Q_{k_2}, *if* $\{Q_{k_1} \cup Q_{k_2}\} \triangleright_p \{Q_{k_1}, Q_{k_2}\} \begin{cases} \{Q_{k_1} \cup Q_{k_2}\} \triangleright_p \{Q_{k_1}, Q_{k_2}\} \\ \{Q_{k_1} \cup Q_{k_2}\} \notin h(\bar{Q}) \end{cases}$;
Split rule: split any coalitions $\{Q_{k_1}, Q_{k_2}\}$ *into two coalitions* Q_{k_1},Q_{k_2}, *if* $\{Q_{k_1} \cup Q_{k_2}\} \triangleright_p \{Q_{k_1}, Q_{k_2}\} \begin{cases} \{Q_{k_1}, Q_{k_2}\} \triangleright_p \{Q_{k_1} \cup Q_{k_2}\} \\ \{Q_{k_1}, Q_{k_2}\} \notin h(\bar{Q}) \end{cases}$, *where* $\triangleright_p$ *denotes the pareto order,* $h(\bar{Q})$ *denotes the history clustering information.*

The network partition is first initialized to $Q^0 = \{\{1\}, \ldots, \{|\mathcal{Q}|\}\}$, i.e., each BS separately serves its attached users. When the ICI is severe, the BSs have the incentive to cooperate with dominating interferer to jointly serve users, thus the EE is improved. After initialization, merge and split operations are performed to iteratively obtain the optimal partitions. At each iteration, the proposed energy efficient beamforming algorithm (Algorithm 1) is used to determine the cooperative transmission strategy and calculate the achieved EE. In this way, we can obtain the EE optimal clusters and relevant beamformer through hierarchical iteration.

Since the total number of the partitions is finite, i.e., Bell number and history clustering information is introduced into the algorithm to avoid the repetitive deviations, the proposed cluster forming algorithm always converges with any initial partition. In addition, according to Theorem 6.2 [2], the proposed cluster forming algorithm is $\mathbb{D}_{hp}$-stable.

4 Numerical Results

In this section, performance of the proposed energy efficient clustering and beamforming algorithm for cooperative multicell networks are numerically evaluated. As shown in Fig. 1(a), we consider a multicell systems with 7 uniformly distributed BSs each equipped with 2 antennas. Users are attached to BSs whose pilot signal is strongest. At each time slot, we assume that each BS only serves one single-antenna user. The channel from BS q_l to user i_k is assumed to be $\mathbf{H}_{i_k}^{q_l} = \sqrt{f_{i_k,ls}^{q_l}}\mathbf{H}_{i_k,ss}^{q_l}$, where $\mathbf{H}_{i_k,ss}^{q_l}$ is small scale fading coefficient and is modeled as the Gaussian distribution with zero mean and unit covariance. $f_{i_k,ls}^{q_l}$ represents the large scale fading coefficient and is modeled as $f_{i_k,s}^{q_l} - 15.3 - 37.6\log_{10}(d_{i_k}^{q_l})$, where $f_{i_k,s}^{q_l}$ denotes the shadow fading in decibels. For comparison, some baseline strategies are also simulated: (1) the proposed energy efficient beamforming algorithm with no cooperation. (2) the proposed energy efficient beamforming algorithm with full cooperation. (3) the maximum ratio transmission (MRT) with no cooperation. (4) MRT with proposed clustering algorithm.



(a) (b) (c)

Fig. 1. (a) Simulated cooperative multicell network model (a) Energy efficiency vs transmit power constraint: when flexible cooperation is considered (b) Energy efficiency vs transmit power constraint: comparison with full cooperation case.

Figure 1(b) shows the EE with different transmit power constraint. It can be seen that when applying the proposed energy efficient beamforming algorithm, the EE can be greatly improved compared with MRT case and the gain can be up to 104%. Moreover, when the CFG based clustering algorithm is also exploited, the EE can be further improved by 20.5%. In addition, we can see that with the increase of the transmit power constraint, the EE first increases and then decreases. This is due to the increased ICI and transmit power. Figure 1(c) shows the EE performance with different degree of cooperation. Full cooperation of multicells will improve the network capacity, however, it leads to increased energy consumption, and hence results in EE degradation. Comparing with full cooperation, the proposed CFG based clustering algorithm enables more flexible cooperation. When the ICI is severe, BSs will cooperate with aggressor BSs to improve the EE. Hence the proposed algorithm shows superior performance against the full cooperation.

5 Conclusion

In this paper, we considered joint clustering and beamforming for energy efficiency optimization in cooperative multicell networks. In the dense network scenario, each BSs separately serve their attached UEs may not be energy efficient due to the severe intercell interference. So some BSs may be prompted to cooperative with interfering neighbor BSs in order to improve the energy efficiency. Hence in this paper, the hierarchical iterative strategy is proposed to fulfill the goal of flexible cooperation. The EE optimization problem is divided into two coupled subproblem. CFG is used to obtain the EE-optimal network partition. For beamforming problem, based on the fractional program and the MMSE model, the EE optimization problem is transformed to a convex optimization problem and is efficiently solved. For the future work, we will consider the user scheduling and extend the algorithm into heterogeneous cloud radio access networks.

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