Wireless Pers Commun (2016) 86:351–365
DOI 10.1007/s11277-015-3118-3

Multiple Base Stations Cooperation: A Novel Clustering Algorithm and Its Energy Efficiency

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Published online: 20 November 2015

Abstract Multiple base stations (BSs) cooperation can effectively reduce the inter-cell interference and especially improve the performance of the cell-edge users, which has been regarded as an important technology in future wireless communication system. All BSs full cooperation is unaffordable for system overhead, so how to partition the BSs in the system into different clusters to cooperate with a low complexity is a challenging issue. In this paper, a novel dynamic clustering algorithm for multiple BSs cooperation in downlink is proposed, and system energy efficiency (EE) is investigated. Firstly, with equal power allocation per symbol and per antenna equal power constraint, the formulas of spectral efficiency (SE) and EE for the case of ideal transmit and the case of actual transmit are derived, respectively. In addition, a novel dynamic clustering algorithm based on channel norm is presented. By calculating the mutual interference matrix according to channel norm, for each clustering judgment, the BS which has the biggest element in the present interference matrix is selected as the leader BS. Then the rest BSs which have the larger interference coefficient with the leader BS are chosen to joint the cluster until the cluster is formed. The computational complexity of the proposed algorithm is analyzed. Simulation results show that EE of the proposed algorithm is better than that of the static clustering one and slightly worse than that of the decentralized algorithm but with a lower complexity.

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Keywords Multiple base stations cooperation · Dynamic clustering · Energy efficiency

1 Introduction

Multiple base stations (BSs) cooperation, which can be called multi-cell cooperation, network MIMO, coordinated multi-point (CoMP) in wireless communication system, has been extensively studied [1–4]. By sharing the channel state information (CSI) and user data information over the backhaul links, several BSs in the same cluster jointly pre-code and transmit signals, the inter-cell interference can effectively be reduced or even be eliminated. In theory, the more the collaborative BSs are, the larger the system capacity gain is [5]. However, in fact, it is difficult for too many BSs to coordinate, and there are some requirements that need to be solved, such as the limited capacity constraints of backhaul links between the BSs [6, 7], the perfect CSI feedback overhead from the users to the BS [8], latency control for network synchronization [9], and so on. The most effective solution is to partition the BSs in the system into some separate groups, i.e., clusters. The common used methods include static clustering and dynamic clustering.

The works on the dynamic clustering of BSs mainly focus on the system capacity, while the complexity of the well-known dynamic clustering algorithm is high. Most energy efficiency (EE) solutions are based on static clustering [6, 10] or single cell [11, 12]. As far as we know, EE for dynamic clustering in downlink is rarely studied. The static clustering method is adopted in [13], and the optimal cluster sizes for EE in four different scenarios are discussed. The effects of BS sleep mode and multiple BSs cooperation on the cluster size are presented, in addition, the minimum user data rate requirement, the BS transmit power and the consumption of the signal processing can also have influences on the cluster size. The relationship between the effective capacity and the total energy consumption in the actual system is studied in [14]. In addition to the transmit power, the total energy consumption also includes the power due to signal processing and the backhaul overhead. For a given cluster size, in order to maximize the sum capacity of downlink and uplink, the exhaustive search method is used to achieve the best clustering results for each channel realization. A dynamic clustering algorithm with fixed cluster size in downlink is proposed in [15], and the cluster set changes over time in order to maximize system capacity. This algorithm has a higher capacity than that of the static clustering. However, this algorithm is a brute force search algorithm, which needs to calculate the system capacity of all the possible cluster sets. The computational complexity of this algorithm and the system overhead grow exponentially with the number of BSs. Another dynamic clustering algorithm is presented in [16], and the whole system is divided into several fixed large clusters, then each large cluster is divided into several sub-clusters, and the sub-clusters constitute the candidate patterns. The candidate pattern which has the maximal system capacity is considered as the optimal clustering set. Although this algorithm reduces the computational complexity, the system gain is limited. Therefore, how to find a low complex clustering algorithm for multiple BSs cooperation is a challenging issue.

In this paper, system EE with dynamic clustering is investigated, and a novel dynamic clustering algorithm for multiple BSs cooperation is proposed. With equal power allocation and per antenna equal power constraint, the formulas of system spectral efficiency (SE) and EE for the case of ideal transmit [17] and the case of actual transmit are derived, respectively. The lower bound and the upper bound for SE and EE are addressed. By calculating the mutual interference matrix according to channel norm, the BS which has the biggest element in the interference matrix is selected as the leader BS. Then the rest BSs are chosen by the leader BS according to the cluster size to form a new cluster. Compared with the known dynamic clustering algorithm, the proposed algorithm has the very low complexity.

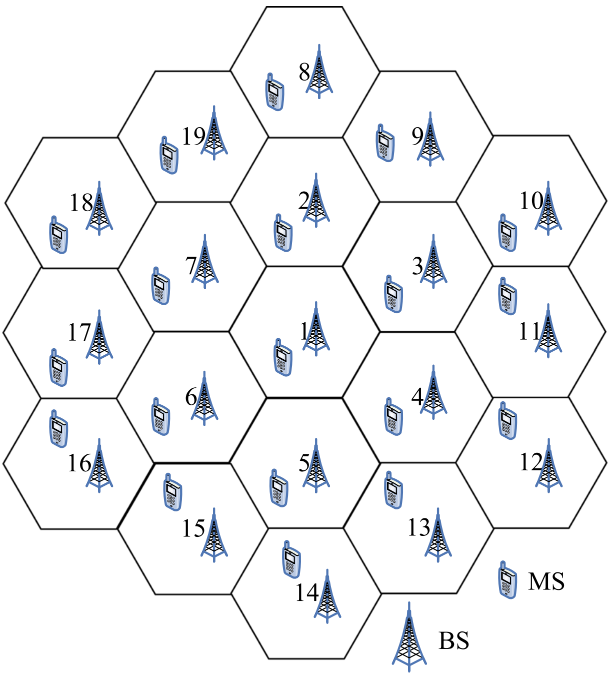
The rest of this paper is organized as follows. In Sect. 2, the system model is introduced. In Sect. 3, SE and EE for the lower bound and the upper bound are derived, where the case of ideal transmit and the case of actual transmit are considered, respectively. In Sect. 4, a novel dynamic clustering algorithm based on channel norm is proposed, and the computational complexity is analyzed. Simulation results are presented in Sect. 5. Finally, conclusions are drawn in Sect. 6.

Notations: Bold upper and lower case letters are used to denote matrices and vectors, respectively. $(\cdot)^T$ and $(\cdot)^{\mathcal{H}}$ stand for transpose and Hermitian transpose, respectively. $\mathbb{C}^N$ stands for the N dimensional complex vector space. $\mathbb{E}[\cdot]$ denotes the expectation operator, and the trace is expressed by $\mathrm{tr}(\cdot)$. $\lceil x \rceil$ denotes the nearest integers greater than or equal to x.

2 System Model

A wireless cellular system in downlink with M BSs and K mobile stations (MSs) is used for analysis, and the frequency reuse factor is 1, which is shown in Fig. 1, and a single antenna is equipped for each BS and MS, respectively. The channel state information (CSI) is shared in the main center processing unit, then the BSs in the system are partitioned into several clusters, and the cluster size can be the same, also can not be the same. The number

Fig. 1 Network model



of the clusters for each cluster set is G, and the g-th cluster is M_g, so $\bigcup_{g=1}^{G} \left|M_g\right| = M$, where $2 \leqslant M_g \leqslant M$. For simplicity, it is assumed that the cluster size in one cluster set is the same. If the cluster size is Ω, and the number of cluster is $\lceil M/\Omega \rceil$. One thing to note here is that each BS can only be in one cluster, and the MS in the cell can only be served by the corresponding cluster. Let K_g denote the MSs set served by the g-th cluster, and $\bigcup_{g=1}^{G} \left|K_g\right| = K$. The channel for the i-th MS in the j-th cluster is

$$\mathbf{h}_{K_{j(i)}} = \left[\mathbf{h}_{K_{j(i)}}^{M_1}, \mathbf{h}_{K_{j(i)}}^{M_2}, \ldots, \mathbf{h}_{K_{j(i)}}^{M_G}\right], \tag{1}$$

where $\mathbf{h}_{K_{j(i)}}^{M_g} \in \mathbb{C}^{1\times\left|M_g\right|}, (i = 1, \ldots, \left|K_j\right|, j = 1, \ldots, G, g = 1, \ldots, G)$ is the channel vector from the g-th cluster to the i-th MS in the j-th cluster. Therefore, the whole downlink channel matrix of the system is

$$\mathbf{H} = \left[\mathbf{h}_{K_{1(1)}}^T, \ldots, \mathbf{h}_{K_{1(\left|K_1\right|)}}^T, \ldots, \mathbf{h}_{K_{G(1)}}^T, \ldots, \mathbf{h}_{K_{G(\left|K_G\right|)}}^T\right]^T. \tag{2}$$

When the MS data and CSI are known by the BSs in the same cluster, BSs can transmit the data by jointly processing. The common used precoding techniques include dirty paper coding (DPC), zero-forcing (ZF) precoding, and minimum mean squared error (MMSE) precoding, and ZF precoding is adopted in this paper. The ZF precoding matrix for the j-th cluster is $\mathbf{V}_{K_j} = [\mathbf{v}_{K_{j(1)}}, \mathbf{v}_{K_{j(2)}}, \ldots, \mathbf{v}_{K_{j(|K_j|)}}]$, where $\mathbf{v}_{K_{j(i)}} \in \mathbb{C}^{\left|M_j\right|\times 1}$ is the normalized precoding vector. The transmit data symbol vector is $\mathbf{x}_{K_j} = \left[x_{K_{j(1)}}, x_{K_{j(2)}}, \ldots, x_{K_{j(|K_j|)}}\right]^T$, where $\mathbb{E}\left[|x_{K_{j(i)}}|^2\right]$=1, $i = 1, \ldots, |K_j|$, and the allocated power vector is $\mathbf{s}_{K_j} = \left[s_{K_{j(1)}}, s_{K_{j(2)}}, \ldots, s_{K_{j(|K_j|)}}\right]^T$. Therefore, the received signal for the i-th MS in the j-th cluster is

$$\begin{aligned} y_{K_{j(i)}} &= \mathbf{h}_{K_{j(i)}}^{M_j} \mathbf{v}_{K_{j(i)}} \sqrt{s_{K_{j(i)}}} x_{K_{j(i)}} \\ &+ \sum_{l=1, l\neq i}^{\left|K_j\right|} \mathbf{h}_{K_{j(i)}}^{M_j} \mathbf{v}_{K_{j(l)}} \sqrt{s_{K_{j(l)}}} x_{K_{j(l)}} \\ &+ \sum_{q=1, q\neq j}^{G} \sum_{m=1}^{\left|K_q\right|} \mathbf{h}_{K_{j(i)}}^{M_q} \mathbf{v}_{K_{q(m)}} \sqrt{s_{K_{q(m)}}} x_{K_{q(m)}} + n_i, \end{aligned} \tag{3}$$

where $\sqrt{U_{K_{j(i)}}} = \mathbf{h}_{K_{j(i)}}^{M_j} \mathbf{v}_{K_{j(i)}} \sqrt{s_{K_{j(i)}}} x_{K_{j(i)}}$ is the useful received signal, $\sqrt{I_{K_{j(i)}}^{tra}} = \sum_{l=1, l \neq i}^{|K_j|} \mathbf{h}_{K_{j(i)}}^{M_j} \mathbf{v}_{K_{j(l)}} \sqrt{s_{K_{j(l)}}} x_{K_{j(l)}}$ is the interference signal from the other BSs of the intra-cluster, $\sqrt{I_{K_{j(i)}}^{ter}} = \sum_{q=1,q\neq j}^{G} \sum_{m=1}^{\left|K_q\right|} \mathbf{h}_{K_{j(i)}}^{M_q} \mathbf{v}_{K_{q(m)}} \sqrt{s_{K_{q(m)}}} x_{K_{q(m)}}$ is the interference signal from the BSs of the other clusters, and n_i is the additive white Gaussian noise (AWGN) with zero mean value and variance $\mathbb{E}\left(n_i n_i^H\right) = \sigma^2$. Unlike the traditional total power constraint, the case of per antenna power constraint is adopted in this section. This is because in practical wireless system, each antenna has its own power amplifier (PA), and the output power of each antenna is controlled by its PA type [18, 19]. Therefore, the power constraint for the m-th antenna in the j-th cluster is

$$\sum_{n=1}^{|K_j|} \left|\mathbf{V}_{K_j(m,n)}\right|^2 s_{K_{j(n)}} \leqslant P_m, \quad m = 1, 2, \ldots, |M_j|. \tag{4}$$

It is assumed that, in the j-th cluster, each symbol is allocated to the same power and each antenna has the same power constraint, i.e., $s_{K_{j(i)}} = S, i = 1, \ldots, |K_j|$ and $P_m = P, \quad m = 1, 2, \ldots, |M_j|$. Thus, the relation between the symbol power and the antenna power constraint is as follows

$$S = P / \max_{m=1,2,\ldots,|M_j|} \left[\mathbf{V}_{K_j}(\mathbf{V}_{K_j})^{\mathcal{H}}\right]_{(m,m)}. \tag{5}$$

3 Derivation of SE and EE

For a given cluster realization, system SE and EE are derived, respectively. When a cluster realization forms, for the MSs in the j-th cluster, the sum of the achieved throughput is expressed as $R(M_j)$. There are a variety of metrics which are used to measure system EE [20, 21]. In this paper, the system throughput per unit energy consumption, i.e., the bits per Joule, will be used as the metric of system EE. The system sum-throughput is

$$R = \sum_{j=1}^{G} R(M_j). \tag{6}$$

The system SE ψ is

$$\psi = \sum_{j=1}^{G} R(M_j)/M. \tag{7}$$

So the system EE η is

$$\eta = \frac{R}{P_{total}} = \frac{\sum_{j=1}^{G} R(M_j)}{P_{total}}, \tag{8}$$

where P_{total} is the total power consumption of the system.

3.1 System SE and EE for Ideal Transmit

Here, system SE and EE for the case of ideal transmit are considered, respectively. The ideal transmit means that only the radio frequency (RF) output power is considered, and the circuit power consumption of BS, the power amplifiers dissipation and the energy consumption of the backhaul links will not be included. When the cluster is formed, with equal power allocation and per antenna equal power constraint, system SE in each time slot is

$$\psi_l = \sum_{j=1}^{G} \sum_{i=1}^{|K_j|} \log_2\left(1 + \frac{U_{K_{j(i)}}}{I^{tra}_{K_{j(i)}} + I^{ter}_{K_{j(i)}} + \sigma^2}\right) \Bigg/ M \tag{9}$$

and (9) is a lower bound of SE for a given clustering method because of the inter-cluster interference. On the other hand, when there is no inter-cluster interference, the upper bound of SE can be given as follows

$$\psi_u = \sum_{j=1}^{G} \sum_{i=1}^{|K_j|} \log_2 \left(1 + \frac{U_{K_{j(i)}}}{I_{K_{j(i)}}^{tra} + \sigma^2} \right) \Bigg/ M \tag{10}$$

Let $\theta_{(M_j)} = 1 / \max_{m=1,2,\ldots,|M_j|} [\mathbf{V}_{K_j} (\mathbf{V}_{K_j})^{\mathcal{H}}]_{(m,m)}$, according to the definition of EE, system EE for the ideal transmit is

$$\eta_l = \frac{\sum_{j=1}^{G} \sum_{i=1}^{|K_j|} \log_2 \left(1 + \frac{U_{K_{j(i)}}}{I_{K_{j(i)}}^{tra} + I_{K_{j(i)}}^{ter} + \sigma^2} \right)}{P \left(\sum_{j=1}^{G} \mathrm{tr}(\mathbf{V}_{K_j} (\mathbf{V}_{K_j})^{\mathcal{H}}) \theta_{(M_j)} \right)}, \tag{11}$$

Due to the inter-cluster interference, (11) is a lower bound of EE for the ideal transmit. Similarly, if there is no inter-cluster interference, the upper bound of EE can be given

$$\eta_u = \frac{\sum_{j=1}^{G} \sum_{i=1}^{|K_j|} \log_2 \left(1 + \frac{U_{K_{j(i)}}}{I_{K_{j(i)}}^{tra} + \sigma^2} \right)}{P \left(\sum_{j=1}^{G} \mathrm{tr}\left(\mathbf{V}_{K_j} (\mathbf{V}_{K_j})^{\mathcal{H}}\right) \theta_{(M_j)} \right)}. \tag{12}$$

3.2 System SE and EE for Actual Transmit

The ideal transmit only considers the RF power, which only contains a small part of the overall power consumption of the whole system, and therefore may result in one-sides conclusion, when evaluating system EE [22]. The power consumption models which includes different components for macro and micro BSs are presented in [23], and the backhaul link power is discussed. The actual total energy consumption for a given cluster size can be classified into three categories: the total power amplifiers energy dissipation, the circuit consumption due to signal processing and the backhaul link energy consumption [10]. Therefore, the actual power model of the j-th cluster is

$$P_{act(j)} = \sum_{i=1}^{|M_j|} p_i / \xi + P_c |M_j| + P_b N_{b(M_j)}, \tag{13}$$

where p_i represents the transmit output power of the i-th power amplifier, and $\xi \in [0, 1]$ is the power amplifier efficiency. P_c is the circuit power consumption value of a BS, which is caused by base band digital signal processing, the active transceiver filter, digital to analog converter (DAC), analog to digital converter (ADC), the frequency synthesizer, and so on. P_b is the additional power requirement per backhaul link. $N_{b(M_j)}$ is the number of backhaul links of the j-th cluster, which is related to the network structure.

The system SE for the case of actual transmit is the same as that for the ideal transmit. In this case, the power P is replaced by the output power of the power amplifier. The system EE for the actual power model is

$$\tilde{\eta}_l = \frac{\sum_{j=1}^{G}\sum_{i=1}^{|K_j|}\log_2\left(1+\frac{U_{K_{j(i)}}}{I^{tra}_{K_{j(i)}}+I^{ter}_{K_{j(i)}}+\sigma^2}\right)}{\sum_{j=1}^{G}\mathrm{tr}(\mathbf{V}_{K_j}(\mathbf{V}_{K_j})^{\mathcal{H}})\theta_{(M_j)}P/\xi+P_c|M_j|+P_bN_{b(M_j)}}, \tag{14}$$

and (14) is a lower bound of EE for the actual transmit because of the inter-cluster interference. When there is no inter-cluster interference, the upper bound of EE is

$$\tilde{\eta}_u = \frac{\sum_{j=1}^{G}\sum_{i=1}^{|K_j|}\log_2\left(1+\frac{U_{K_{j(i)}}}{I^{tra}_{K_{j(i)}}+\sigma^2}\right)}{\sum_{j=1}^{G}\mathrm{tr}(\mathbf{V}_{K_j}(\mathbf{V}_{K_j})^{\mathcal{H}})\theta_{(M_j)}P/\xi+P_c|M_j|+P_bN_{b(M_j)}}. \tag{15}$$

When the cluster size and the CSI are given, with equal power allocation and per antenna equal power constraint for a cluster set, EE for the actual transmit is the function of the output power of the power amplifier. When the range of the output power of the PA is given, it is an one dimensional optimization problem to solve EE. The problem can be solved by search methods and/or approximation methods, and the detailed process can be found in [24].

4 Proposed Dynamic Clustering Algorithm

By BSs clustering, system performance can be improved, which mainly because the inter-cell interference in the cluster can be alleviated or eliminated. There are two main kinds of clustering methods, i.e., static clustering method and dynamic clustering method.

4.1 Static Clustering

For static clustering, the cluster realization is formed according to the geographic locations of the BSs. The selected BSs in the cluster are fixed, which does not change over time. The advantage of this method is that the clustering course is simple, and the main center processing unit do not need the overhead of backhaul. However, there is severe inter-cluster interference when the scheduled MSs is on the edge of the two adjacent clusters.

4.2 Dynamic Clustering

In order to solve the defect of static clustering, BSs dynamic clustering has raised concerns [15, 16, 25–27]. Although the optimal system performance can be achieved by exhaustive search, the complexity is too high. In [28], a downlink decentralized dynamic clustering algorithm is proposed. Each BS selects the BSs from the neighboring cells, then these BSs compose several clusters. These clusters form the clusters list according to the corresponding cluster capacity in descending order, and the cluster with the maximum capacity is proposed as the preferred cluster. In the process of iteration, if the BSs in the preferred cluster have been received by other clusters, the cluster with the second maximum sum capacity is selected as the preferred cluster, and so on.

4.3 The Proposed Dynamic Clustering Algorithm

In this subsection, a novel dynamic clustering algorithm is proposed. The higher the interference between two BSs is, the more likely they are in the same cluster. Motivated by this, a new algorithm based on the channel norm is constructed, and it turns out that the number of the candidate cluster sets for this algorithm decreases dramatically.

For the multi-cell system with M BSs and K MSs, it is assumed that the cluster size is Ω. Let $\mathcal{D}$ denote the candidate BSs list, which contains all the BSs which have not been selected to form a new cluster. Let $\widetilde{\mathcal{D}}$ denote the selected BSs list, which includes all the BSs which have been selected in the cluster forming. According to the whole channel matrix $\mathbf{H}$, the mutual interference matrix $\mathbf{F}$ is defined as follows

$$f_{ij} = \begin{cases} |h_{ij}|^2 + |h_{ji}|^2 & \text{for } i \neq j \\ 0 & \text{for } i = j \end{cases} \tag{16}$$

where f_{ij} is the element in the i-th line and the j-th column in $\mathbf{F}$, and h_{ij} is the channel coefficient from the i-th BS to the j-th MS. It can be seen that $\mathbf{F}$ is a symmetric matrix, so we only need to calculate the elements in the upper triangular or the lower triangular of $\mathbf{F}$.

The main step of the proposed algorithm is to find the lead BS for each cluster. For the BS i in $\mathcal{D}$, if i satisfies $\max\limits_{i \in \mathcal{D}} \sum_{j, j \neq i} f_{ij}$, then BS i is selected as the lead BS. The rest of the candidate BSs are selected by the lead BS. If the BS i' satisfies $\max\limits_{i' \in \mathcal{D}} f_{ii'}$, then the BS i' is selected to join the current cluster. When a new cluster is formed, the selected BSs are deleted from $\mathcal{D}$ and are added to $\widetilde{\mathcal{D}}$. Another cluster is formed according to the same steps until all BSs are partitioned into separate clusters. The algorithm is summarized in Table 1.

As was mentioned earlier, the complexity of exhaustive search increases rapidly with the number of BSs. For convenience, we only analyze the number of possible cluster sets.

Table 1 The Proposed Dynamic Clustering Algorithm

1: Initialize arguments, including the number of BSs M, the cluster size Ω, the number of the clusters G, the candidate BSs list $\mathcal{D}$, the selected BSs list $\widetilde{\mathcal{D}}$.

2: Calculate the mutual interference matrix $\mathbf{F}$ according to the channel matrix $\mathbf{H}$.

If $i \neq j, f_{ij} = |h_{ij}|^2 + |h_{ji}|^2$; else if $i = j, f_{ij} = 0$.

3: for $g = 1:1:G$

4: for $\omega = 1:1:\Omega$

5: if $\omega = 1$, select the BS i that satisfies $\max\limits_{i \in \mathcal{D}} \sum\limits_{j, j \neq i} f_{ij}$, and BS i is the lead BS of cluster M_g.

Then update $\mathcal{D}$ and $\widetilde{\mathcal{D}}$ as follows: $\mathcal{D}=\mathcal{D}-\{i\}$; $\widetilde{\mathcal{D}}=\widetilde{\mathcal{D}}+\{i\}$.

6: else if $\omega \neq 1$, select BS i' that satisfies $\max\limits_{i' \in \mathcal{D}} f_{ii'}$, and let BS i' join the cluster M_g.

Then update $\mathcal{D}$ and $\widetilde{\mathcal{D}}$, $\mathcal{D}=\mathcal{D}-\{i'\}$, $\widetilde{\mathcal{D}}=\widetilde{\mathcal{D}}+\{i'\}$.

7: end if

8: end for

9: end for

10: Calculate the cluster set $\{M_1, M_2, \cdots, M_G\}$.

Assume $\Gamma = M/\Omega$ is an integer. Then, there are $M!/((\Omega!)^{\Gamma}\Gamma!)$ possible cluster sets for exhaustive search [15]. In sharp contrast, our proposed algorithm incurs a very low computational load. Once the lead BS of a cluster is chosen, the cluster can be formed. For example, when $M = 18, \Omega = 3, \Gamma = 6$, the number of the cluster sets for exhaustive search is 90,590,400. The average number of clusters in each BS for the decentralized dynamic clustering algorithm is 1.9, so the average number of cluster sets for the decentralized algorithm in [28] is 36. In fact, the number of cluster sets for this algorithm would be greater than 36, because each BS needs to search the candidate clusters from the neighboring cells. On the other hand, our proposed algorithm only needs one cluster set, which can be decided once by calculating the channel norm, regardless of the number of the BSs in system.

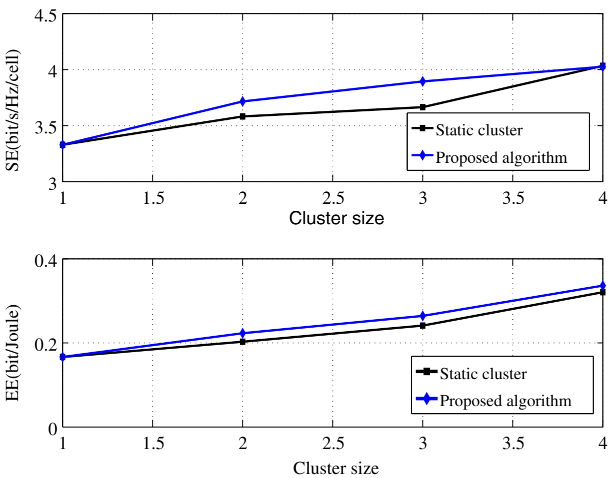
5 Simulation Results

A two rings cellular network in downlink is considered, as shown in Fig. 1. For the convenience of clustering, a BS in the second ring is omitted. The radius of the hexagon cell is 500 meters, and each BS equipped with one omnidirectional antenna locates at the center of its own cell. Single antenna MSs are randomly distributed in each cell, and only one MS in each cell is served in each time of simulation. The channel coefficient from the m-th BS to the k-th MS is

$$h_{m,k} = \sqrt{G_a} h^l_{m,k} h^s_{m,k}, \tag{17}$$

where $G_a = 7.94$ is the power gain which includes the transmit antenna in BS and the receive antenna in MS. $h^l_{m,k} = \sqrt{\lambda_{m,k}/d^{\alpha}_{m,k}}$ represents the combination of path loss and shadow fading, and $\lambda_{m,k}$ is a log-normal distributed shadowing variable with zero mean and standard deviation σ_{sh}, here $\sigma_{sh} = 8$ dB. $d_{m,k}$ is the distance from the m-th BS to the k-th MS, and $\alpha = 3.76$ represents the path loss exponent. $h^s_{m,k}$ represents the Rayleigh small scale fading [25, 29].

Fig. 2 System SE and EE versus cluster size for static cluster and the proposed dynamic clustering algorithm, where the inter-cluster interference is considered



In order to assess EE of the wireless system comprehensively, besides RF power, the other energy consumption such as the circuit power consumption of BS and the backhaul link power should be considered. It is assumed that the efficiency of the power amplifier is 0.35, each BS circuit power consumption is 10 W, the backhaul links are connected with the fiber, and the average power consumption for each backhaul link is 10 W.

Figure 2 illustrates system SE and EE as a function of the cluster size for static cluster and the proposed dynamic clustering algorithm, respectively, and the inter-cluster interference is considered. The ideal transmit RF power is 20 W. When the cluster size is 1, there is no cooperation between BSs, hence this point on the curve represents the lowest performance. When the cluster size increases, SE and EE all increase. This is because with the increase of the cluster size, the inter-cell interference (ICI) can be better reduced. SE and EE of the proposed dynamic clustering algorithm are better than that of static cluster when the cluster size is 2 and 3. However, since the cluster of proposed algorithm is determined by the leader BS, which may separate some BSs, and SE of the cluster size 4 degrades, but system EE is still better than that of static cluster. Because of the feedback and backhaul consumption, the cluster size is limited in real system, so the cluster size 2 or 3 is suitable.

System SE and EE of the proposed algorithm for different cluster sizes versus the ideal transmit power are shown in Fig. 3, and the inter-cluster interference is considered. For system SE, in low transmit power regime, zero-forcing precoding results in system capacity degradation. When the ideal transmit power is larger than 10 dBW, the proposed algorithm is better than no-cooperation, and the larger the cluster size, the higher the system SE. When the ideal transmit power is larger than 20 dBW, system SE does not increase linearly, this is because the inter-cluster interference is serious. System EE decreases with the transmit power.

Then system SE and EE of the proposed algorithm versus the actual transmit power for some cluster sizes are shown in Fig. 4, in which the inter-cluster interference is considered. It can be seen that when the output power of power amplifier is smaller than 36 dBW, system EE of the proposed dynamic clustering algorithm is worse than that of no-cooperation. One reason is that in low transmit power region, zero-forcing precoding results in system capacity degradation, which also affects the system EE; the other reason is that, the circuit and the backhaul links also consume the power. When the output power of power

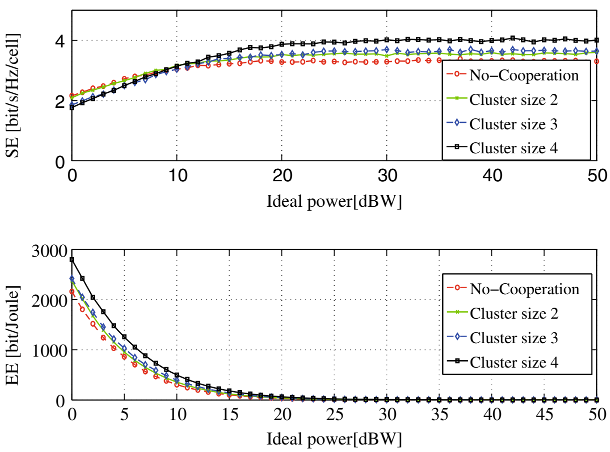


Fig. 3 System SE and EE of the proposed algorithm versus the ideal transmit power, where the inter-cluster interference is considered

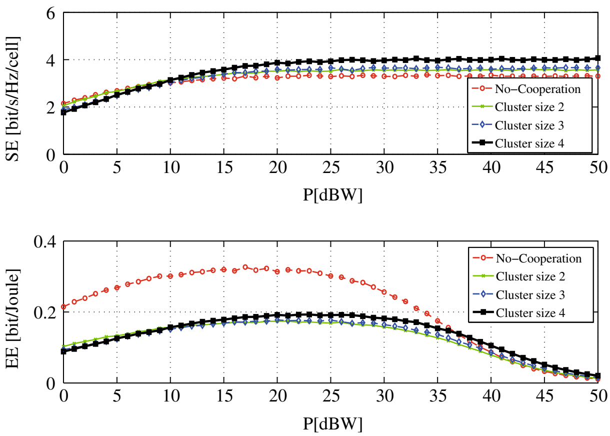


Fig. 4 System SE and EE of the proposed algorithm versus the actual transmit power, where the inter-cluster interference is considered

amplifier is larger than 36 dBW, system EE of the proposed algorithm is better than that of no-cooperation, and the larger the cluster size, the better the system EE.

In Fig. 5, system SE and EE versus the actual transmit power for static cluster, the proposed algorithm and the decentralized algorithm [28] are shown, and the cluster size is 3. When the inter-cluster interference is considered, system SE and EE evaluations are the same as Fig. 4. When there is no inter-cluster interference, system SE increases with the transmit power, and system EE slightly increases with the transmit power at first, then decreases with the transmit power, so there is a maximum EE value.

The tradeoff between SE and EE for static cluster, the proposed algorithm and the decentralized algorithm can be seen in Fig. 6, and the cluster size is 3. When the inter-cluster interference is considered, system SE and EE increase gradually at first, then SE reaches the maximum values that smaller than 4 bit/s/Hz/cell, and the maximum EE value is smaller than 0.2 bit/Joule. With the power increasing, SE remains a constant and EE decreases. When there is no inter-cluster interference, SE increases from 2 bit/s/Hz/cell to more than 16 bit/s/Hz/cell in the transmit power region, EE increases from 0.1 to 0.48 bit/

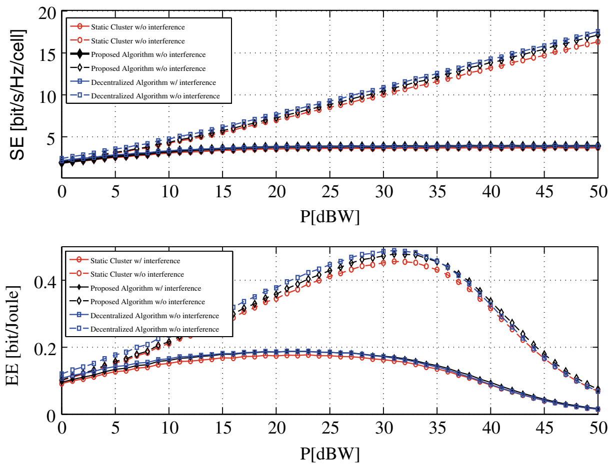


Fig. 5 System SE and EE versus the actual transmit power for static cluster, the proposed algorithm and the decentralized algorithm when the cluster size is 3

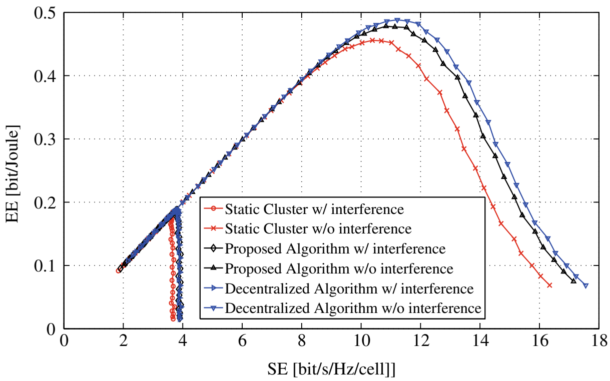


Fig. 6 The tradeoff between SE and EE for static cluster, the proposed algorithm and the decentralized algorithm when the cluster size is 3

Joule, then decreases gradually. It can be seen that the inter-cluster interference has an important influence on SE and EE, so the methods to eliminate interference such as fractional frequency reuse (FFR), orthogonal frequency division multiplexing (OFDM) are beneficial to improve SE and EE. However, there is a saturation point for SE–EE curve. EE will not increased, regardless of how much transmit power is used. It will provide the scientific guidance for the design of the optimal energy consumption networks in future.

6 Conclusions

In this paper, EE based on a novel dynamic clustering algorithm for multiple BSs cooperation has been investigated. The formulas for system SE and EE were derived, respectively, and the case of ideal transmit and actual transmit were considered. A novel dynamic clustering algorithm based on channel norm was proposed, which has a better performance than that of static clustering and a lower complexity than that of a known decentralized algorithm. Simulation results showed that EE of the proposed algorithm is better than that of the static cluster, and slightly degrades than that of the decentralized algorithm. In future work, Interference cancellation such as fractional frequency reuse, power management should be considered jointly with dynamic clustering so as to further improve the system EE.

Acknowledgments This work is supported in part by the National Science Foundation of China (61471115); the National Special Key Program (2014ZX03003010-002); Natural Science Foundation of Jiangsu Province (BK20131299); the National Basic Research Program of China (973 Program 2012CB316004); the National High Technology Research and Development Program of China (863 Program 2012AA011401).

References

1. Gesbert, D., Hanly, S., Huang, H., Shamai, S. S., Simeone, O., & Yu, W. (2010). Multi-cell MIMO cooperative networks: A new look at interference. *IEEE Journal on Selected Areas in Communications*, *28*(9), 1380–1408.
2. Zhang, H., & Dai, H. (2004). Cochannel interference mitigation and cooperative processing in downlink multicell multiuser MIMO networks. *EURASIP Journal on Wireless Communications and Networking*, *2*, 222–235.
3. Zhang, J., & Andrews, J. G. (2010). Adaptive spatial intercell interference cancellation in multicell wireless networks. *IEEE Journal on Selected Areas in Communications*, *28*(9), 1455–1468.

4. Zhang, R. (2010). Cooperative multi-cell block diagonalization with per-base-station power constraints. *IEEE Journal on Selected Areas in Communications*, *28*(9), 1435–1445.
5. Zhang, J., Chen, R., Andrews, J. G., Ghosh, A., & Robert, W. H. J. (2009). Networked MIMO with clustered linear precoding. *IEEE Transactions on Wireless Communications*, *8*(4), 1910–1921.
6. Ng, D. W. K., Lo, E. S., & Schober, R. (2012). Energy-efficient resource allocation in multi-cell OFDMA systems with limited backhaul capacity. *IEEE Transactions on Wireless Communications*, *11*(10), 3618–3631.
7. Tolli, A., Pennanen, H., & Komulainen, P. (2011). Decentralized minimum power multi-cell beamforming with limited backhaul signaling. *IEEE Transactions on Wireless Communications*, *10*(2), 570–580.
8. Huh, H., Tulino, A. M., & Caire, G. (2012). Network MIMO with linear zero-forcing beamforming: Large system analysis, impact of channel estimation, and reduced-complexity scheduling. *IEEE Transactions on Information Theory*, *58*(5), 2911–2934.
9. Mikami, M., Miyashita, M., Miyajima, H., Hoshino, K., Yoshino, H., & Fujii, T. (2012). Field Evaluations on a prototype system of cooperative multi-cell MIMO transmission for asynchronous inter-site base station networks. In *Proceedings of IEEE 75th Vehicular Technology Conference (VTC Spring)* (pp. 1–5).
10. Wang, X., Zhu, P., Sheng, B., & You, X. (2013). Energy-efficient downlink transmission in multi-cell coordinated beamforming systems. In *Proceedings of IEEE Wireless Communications and Networking Conference (WCNC)* (pp. 2554–2558).
11. Ng, D. W. K., Lo, E. S., & Schober, R. (2012). Energy-efficient resource allocation for secure OFDMA systems. *IEEE Transactions on Vehicular Technology*, *61*(6), 2572–2585.
12. Xiong, C., Li, G. Y., Zhang, S., Chen, Y., & Xu, S. (2012). Energy-efficient resource allocation in OFDMA networks. *IEEE Transactions on Communications*, *60*(12), 3767–3778.
13. Han, S., Yang, C., Wang, G., & Lei, M. (2011). On the energy efficiency of base station sleeping with multicell cooperative transmission. In *Proceedings of IEEE 22nd International Symposium on Personal Indoor and Mobile Radio Communications (PIMRC 2011)* (pp. 1536–1540).
14. Fehske, J., Marsch, P., & Fettweis, G. P. (2010). Bit per joule efficiency of cooperating base stations in cellular networks. In *Proceedings of IEEE GLOBECOM Workshops (GC Wkshps)* (pp. 1406–1411).
15. Papadogiannis, A., & Alexandropoulos, G. C. (2010). The value of dynamic clustering of base stations for future wireless networks. In *Proceedings of IEEE International Conference on Fuzzy Systems (FUZZ 2010)* (pp. 1–6).
16. Sun, H., Zhang, X., & Fang, W. (2011). Dynamic cell clustering design for realistic coordinated multipoint downlink transmission. In *Proceedings of IEEE 22nd International Symposium on Personal Indoor and Mobile Radio Communications (PIMRC 2011)* (pp. 1331–1335).
17. Chen, Y., Zhang, S., Xu, S., & Li, G. Y. (2011). Fundamental trade-offs on green wireless networks. *IEEE Communications Magazine*, *49*(6), 30–37.
18. Yu, W., & Lan, T. (2007). Transmitter optimization for the multi-antenna downlink with per-antenna power constraints. *IEEE Transactions on Signal Processing*, *55*(6), 2646–2660.
19. Mai, V. (2011). MISO capacity with per-antenna power constraint. *IEEE Transactions on Communications*, *59*(5), 1268–1274.
20. Hasan, Z., Boostanimehr, H., & Bhargava, V. K. (2011). Green cellular networks: A survey, some research issues and challenges. *IEEE Communications Surveys and Tutorials*, *13*(4), 524–540.
21. Wang, X., Vasilakos, A. V., Chen, M., Liu, Y., & Kwon, T. T. (2012). A survey of green mobile networks: Opportunities and challenges. *ACM Mobile Networks and Applications*, *17*(1), 4–20.
22. Li, X., Wang, H., Meng, C., Wang, X., Liu, N., & You, X. (2013). Total energy minimization through dynamic station-user connection in macro-relay network. In *Proceedings of IEEE Wireless Communications and Networking Conference (WCNC 2013)* (pp. 697–702).
23. Arnold, O., Richter, F., Fettweis, G., & Blume, O. (2010). Power consumption modeling of different base station types in heterogeneous cellular networks. In *Proceedings of IEEE Future Network and Mobile Summit* (pp. 1–8).
24. Andreas, A., & Lu, W. S. (2007). *Practical optimization: Algorithms and engineering applications*. New York: Springer.
25. Liu, J., & Wang, D. (2009). An improved dynamic clustering algorithm for multi-user distributed antenna system. In *Proceedings of IEEE International Conference on Wireless Communications and Signal Processing (WCSP 2009)* (pp. 1–5).
26. Papadogiannis, A., Gesbert, D., & Hardouin, E. (2008). A dynamic clustering approach in wireless networks with multi-cell cooperative processing. In *Proceedings of IEEE International Conference on Communications (ICC 2008)* (pp. 4033–4037).
27. Zhou, S., Gong, J., Niu, Z., Jia, Y., & Yang, P. (2009). A decentralized framework for dynamic downlink base station cooperation. In *Proceedings of IEEE Global Telecommunications Conference (GLOBECOM 2009)* (pp. 1–6).

28. Zhou, S., Gong, J., Jia, Y., & Niu, Z. (2010). A decentralized clustering scheme for dynamic downlink base station cooperation. *IEICE Transactions on Communications*, *93*(12), 3656–3659.
29. You, X., Wang, D., Zhu, P., & Sheng, B. (2011). Cell edge performance of cellular mobile systems. *IEEE Journal on Selected Areas in Communications*, *29*(6), 1139–1150.

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