Cluster-Based Dynamic FBSs On/Off Scheme in Heterogeneous Cellular Networks

Xiaoge Huang(✉), She Tang, Dongyu Zhang, and Qianbin Chen

School of Communication and Information Engineering, Chongqing University of Posts and Telecommunications, Chongqing 400065, China
{Huangxg,Chenqb}@cqupt.edu.cn
{tangshedhl,zhangdongyu}@outlook.com

Abstract. Recent years, with the explosive growth of mobile data traffic, cellular communication system is faced with enormous challenges. The ultra-dense deployment of small cells will increase the network capacity while increasing the energy consumption. In this paper, we study a cluster-based dynamic FBSs on/off scheme in heterogeneous cellular networks, where the overall objective is to maximize the network energy efficiency by optimizing jointly the cell association, the base station on/off strategies and the cluster division, taking into account the load balancing and the QoS requirement of heterogenous cellular networks. The optimization problem is divided into three processes: the base station and the user equipment (UE) association scheme, the femtocell base station (FBS) clustering, and the FBS on/off scheme according to the current traffic load. A cluster-based dynamic FBSs on/off scheme is proposed to improve EE in HCNs while ensuring the load balancing, the probability of outage, and the communication requirement of UEs in the core area. Simulation result shows that the proposed algorithm could achieve significant improvement of the network energy efficiency in all aspects than comparison algorithms in literature.

Keywords: Heterogeneous cellular networks · Energy efficiency
Femtocell base station · Cluster

1 Introduction

Recently, in order to deal with the explosive increment of demand in high speed mobile communication traffic, the network operator urge to seek for various means to increase network capacity. In the traditional cellular network,

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macrocell base stations (MBSs) are used to provide communication service in a wide area. However, the user equipment (UE) located in the marginal of the area will get a low signal-to-interference-plus noise ratio (SINR) and suffer from low communication quality. Accordingly, Small cell is suggested as a kind of local BSs with lower transmission power, which include the microcell base station, the picocell base station (PBS) and the femtocell base station (FBS), while deploying in abundance under the coverage of the MBS to provide higher SINR for cell-edge UEs and further increase capacity of the network. Ultra-dense heterogeneous cellular networks play a critical role in 5G communication system. However, the large amount of small cells could lead to increasing of the extra electric energy consumption. In addition, technologies to enhance network energy efficiency (EE) have become a critical design due to increasing energy price and growing attention toward environmental factors.

There are many challenges in deploying small cell base stations (SBSs) under the coverage of MBS, and various resource allocation schemes have been designed for HCNs [1–4]. Normally, frequency reuse technologies among small cells and macro cells could improve the spectrum efficiency and the capacity of HCNs. In [1], the author proposed a joint subcarrier assignment and power allocation scheme to optimize spectrum efficiency in the downlink transmission of HCNs. Due to the large number of deployed SBSs, a serious co-layer interference will occur in the network. In [2], the author introduced a greedy algorithm to allocate resource blocks under the QoS constraint to reduce interference among FBSs. Especially, it is a feasible method to eliminate interference by clustering. In [3], the author designed clusters through graph-theoretic approaches to eliminate interference in HCNs. In [4], the author applied a modify cluster algorithm and Stackelberg game for resource allocation to improve network throughput.

Moreover, in order to improve EE in the HCN, various schemes have been proposed in [5–7]. In [5], the author designed a dynamic gNB (the name of the BS in 5G) on/off strategy to improve EE, while considering the quality of service (QoS) constraint of UEs and the load balancing among gNBs. The author attempted to explore the relationship of energy efficiency, transmission power and the number of SBSs in [6]. In [7], water-filling method was used to structure the optimal solution of the power allocation problem to further improve EE.

In this paper, we aim to improve EE by clustering with dynamic on/off strategies of FBSs according to the current traffic load, while achieving the optimal tradeoff between the UE SINR threshold and the outage probability in HCNs. The main contributions are summarized as follows:

Firstly, in order to optimize network EE while taking into account the UE SINR requirement, the network outage probability and the load balancing, we propose an optimal UE-FBS association load balancing (UFALB) algorithm.

Secondly, in order to eliminate intra-cluster interference, FBSs are divided into several clusters based on EE and geographic location of FBSs.

Finally, in order to further improve EE, cluster-based FBSs on/off (CBFOO) algorithm is proposed. Notice that, to ensure the communication requirement of UEs in the core transmission area, the FBS can not be turned off if there are UEs in the core transmission area.

The rest of the paper is organized as follows. The system model is presented in Sect. 2. Section 3 provides the cluster formulation and the UE-FBS association strategy. In Sect. 4, the CBFOO algorithm is proposed to improve EE. Simulation results are discussed in Sect. 5. Section 6 draws the conclusion.

2 System Model

2.1 Network Scenario

In this paper, we consider a two-ties HCN which includes the MBS and the FBS for each tier, respectively, as shown in Fig. 1. FBSs are randomly located in the coverage of the MBS. The transmission power of the MBS and the FBS are denoted as P_m and P_f, respectively. The UE will connect with the BS according to UFALB algorithm to obtain the maximum EE. In our scenario, FBSs will be divided into different clusters based on the reactive distance to other FBSs and the different contribution to EE. Accordingly, every cluster will select the cluster head FBS (H-FBS) and member FBSs (M-FBS). The H-FBS could collect all UEs information in the cluster and forward the signaling message to turn on/off M-FBSs to improve NEE. Let **M** denote the set of the MBS, **N** represent the set of the FBS, **K** indicate the set of UEs and **C** denote the set of clusters.

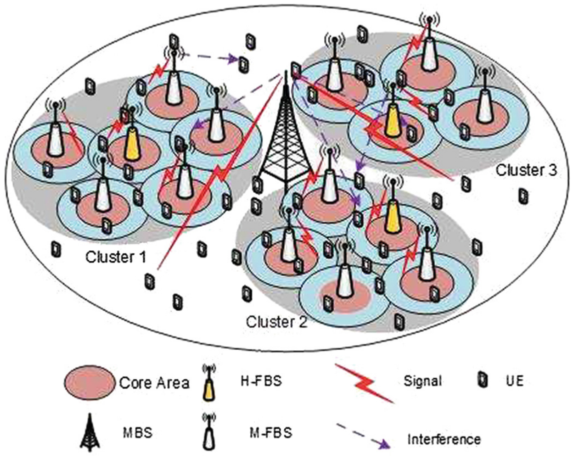

Fig. 1. Network scenario

2.2 Power Consumption and Path Loss Model

A typical FBS hardware model consists of the microprocessor module, the power amplifier (PA) module, the radio frequency (RF) module and the field-programmable gate array (FPGA) module [8]. The power consumption of these modules are represented by P_{mic}, P_{pa}, P_{rf}, and P_{fpga} respectively. Hence, the total power consumption of a FBS is expressed as:

$$P_{total} = P_{mic} + P_{pa} + P_{rf} + P_{fpga} \tag{1}$$

We assume a FBS has two operation modes: "ON" mode and "OFF" mode.

- "ON" mode: the FBS is in full operation, the power consumption is P_{total}.
- "OFF" mode: the FBS is turned off, but it still consumes a little power to maintain the wake-up function.

In this paper, transmission channels are assumed to be time-invariant with slow fading. Thus, the received SINR γ_k^n of UE k from FBS n is calculated by:

$$\gamma_k^n = \frac{P_n L(d_{k,n})\lambda_n}{\sum\limits_{n' \in \mathbf{I}} P_{n'} L(d_{k,n'})\lambda_{n'} + N_0 B} \tag{2}$$

where $\mathbf{I}$ is the set of BSs (e.g. includes the FBS and the MBS) which could generate interference to UE k. P_n is the transmission power of BS n ($n \in \mathbf{I}$). $d_{k,n}$ is the distance between UE k ($k \in \mathbf{K}$) and BS n and B is the bandwidth of the sub-channel. $\lambda_n \in \{0, 1\}$ indicates the operation mode of FBS n, $\lambda_n = 1$ indicates FBS n is in full operation mode, otherwise, $\lambda_n = 0$ indicates FBS n is turned off. $L(\cdot)$ is the path loss function. The path loss model of the MBS and the FBS are expressed as follow:

$$\begin{aligned} L_M(d) &= 34 + 40\log_{10}(d) dB \\ L_F(d) &= 37 + 30\log_{10}(d) dB \end{aligned} \tag{3}$$

3 Cluster Formulation and UE-FBS Association Strategy

3.1 Cluster Formulation

The HCN is considered as an undirected graph $G = \{\mathbf{N}, \mathbf{E}\}$. $\mathbf{N}$ is the set of vertices (regard as FBSs in HCNs). $\mathbf{E}$ is the set of edges between two FBSs. Our purpose is to divide the vertices into different clusters and maximize the following object function [9]:

$$\sum_{(i,j)\in\mathbf{E}_1(\mathbf{N})} \beta w_{i,j}^{+} + \sum_{(i,j)\in\mathbf{E}_2(\mathbf{N})} (1-\beta) w_{i,j}^{-} \tag{4}$$

where $\mathbf{E}_1(\mathbf{N})$ represents the set of edges whose vertices are in the same cluster and $\mathbf{E}_2(\mathbf{N})$ represents the set of edges whose vertices are in the different cluster. $w_{i,j}^{+} = |EE_i - EE_j|$ is the similarity degree between FBS i and FBS j, the greater the EE difference between FBSs, the higher probability they will be divided into the same cluster. $w_{i,j}^{-} = D_{i,j}$ is the difference degree between FBS i and FBS j, which indicates that the smaller the distance between FBSs, the higher probability they be divided into the same cluster. $\beta (0 < \beta < 1)$ represents the weight of w^{+}. According to the above description, the original problem (5) can be expressed as following:

$$
\begin{aligned}
\max_{X} \sum_{i,j \in \mathbf{N}} & \beta \left| EE_i - EE_j \right| x_{i,j} + (1-\beta) D_{i,j} (1 - x_{i,j}) \\
\text{s.t.} \quad & \mathrm{C1}: \quad x_{i,j} = x_{j,i}, \forall i, j \in \mathbf{N} \\
& \mathrm{C2}: \quad x_{i,i} = 1, \forall i \in \mathbf{N} \\
& \mathrm{C3}: \quad x_{i,j} + x_{j,l} + x_{l,i} \leq 1, \forall i, j, l \in \mathbf{N} \\
& \mathrm{C4}: \quad \sum_{j \in \mathbf{N}} x_{i,j} \leq M, \forall i \in \mathbf{N} \\
& \mathrm{C5}: \quad X = (x_{i,j}) \in \{0, 1\}, \forall i, j \in \mathbf{N}
\end{aligned} \tag{5}
$$

C1 denotes that FBS i and j are in the same cluster. C2 represents that a FBS only belongs to one cluster. C3 means if FBS i and j are in the same cluster, meanwhile, FBS j and l are in the same cluster, thus FBS i, j, l are divided into the same cluster. C4 is cluster size constraint. C5 indicates whether FBS i and j are in the same cluster.

There are several approaches to solve the optimization problem (5), such as the traversal search, the Branch and Bound (BnB) scheme, the semidefinite programming (SDP) and so on. However, for ultra-dense networks with a large number of FBSs, the computation complex of the traversal search is too high. Thus, in order to reduce the computational complexity, the SDP-based correlation clustering algorithm [10] is used to obtain the solution:

$$
\begin{aligned}
\max_{X} \sum_{i,j \in \mathbf{N}} & \beta \left| EE_i - EE_j \right| x_{i,j} + (1-\beta) D_{i,j} (1 - x_{i,j}) \\
\text{s.t.} \quad & \mathrm{C1}: \quad x_{i,i} = 1, \forall i \in \mathbf{N} \\
& \mathrm{C2}: \quad x_{i,j} + x_{j,l} + x_{l,i} \leq 1, \forall i, j, l \in \mathbf{N} \\
& \mathrm{C3}: \quad \textstyle\sum_{j \in \mathbf{N}} x_{i,j} \leq M, \forall i \in \mathbf{N} \\
& \mathrm{C4}: \quad x_{i,j} \geq 0, \forall i, j \in \mathbf{N} \\
& \mathrm{C5}: \quad X = (x_{i,j}) \succeq 0, \forall i, j \in \mathbf{N}
\end{aligned} \tag{6}
$$

The constraint C4 indicates that $x_{i,j}$ is slack. In constraint C5, X is a positive semidefinite matrix which is symmetry and non-negative,which can be written as $X = B^T B$, where $B = \{\mathbf{b}_1, \mathbf{b}_2, \cdots, \mathbf{b}_N\}$. Notice that $x_{i,j} = \mathbf{b}_i^T \mathbf{b}_j = \mathbf{b}_i \cdot \mathbf{b}_j$.

Based on the slack solution X of (6), we can obtain a integer solution X_{int} by iterations. Firstly, we obtain L random hyperplane with independent random vectors $\mathbf{r}_y = \{r_{y1}, r_{y2}, \cdots, r_{yN}\}$, $1 \leq y \leq L$, $2^L \geq N$ as their normals. We can divide vertices into the following sets:

$$
\begin{aligned}
& \mathbf{C}_1 = \{i \in \mathbf{N} : \mathbf{r}_1 \cdot \mathbf{b}_i \geq 0, \cdots, \mathbf{r}_L \cdot \mathbf{b}_i \geq 0\} \\
& \mathbf{C}_2 = \{i \in \mathbf{N} : \mathbf{r}_1 \cdot \mathbf{b}_i \geq 0, \cdots, \mathbf{r}_L \cdot \mathbf{b}_i < 0\} \\
& \cdots \\
& \mathbf{C}_{2^L} = \{i \in \mathbf{N} : \mathbf{r}_1 \cdot \mathbf{b}_i < 0, \cdots, \mathbf{r}_L \cdot \mathbf{b}_i < 0\}
\end{aligned} \tag{7}
$$

Accordingly, we can obtain 2^L clusters, such as $\mathbf{C} = \{\mathbf{C}_1, \mathbf{C}_2, \cdots, \mathbf{C}_{2^L}\}$. Thus, we could obtain the optimal solution ZZ_R with X_{int} in (6). Note that $ZZ_R \geq$

$\alpha ZZ_{opt}(\alpha < 1)$, ZZ_{opt} is the optimal solution in (5) and α is related to L. The SDP-based correlation clustering algorithm is summarized as follows.

3.2 UE-FBS Association Strategy

We aim to maximize network energy efficiency of HCNs, while ensuring the outage probability, the load balancing and the UE target-SINR. Therefore, the UE-FBS association load balancing (UFALB) algorithm [9] is introduced to optimize the cell association between FBSs and UEs. The utility function of UE k is composed of access factor θ_k^n and the UE EE_k^n, which is given by:

$$\omega_k^n = \theta_k^n \cdot EE_k^n \tag{8}$$

Algorithm 1 SDP-Based Correlation Clustering Algorithm

1: Solve X in (6) by CVX
2: Calculate $B = \{\mathbf{b}_1, \mathbf{b}_2, \cdots, \mathbf{b}_V\}$ by $X = B^T B$
3: **for** $t = 1 : t_{\max}$ **do**
4: Generate the independent random vectors $\mathbf{r}_i = \{r_{i1}, r_{i2}, \cdots, r_{iV}\}$, $1 \le i \le L$
5: Calculate $\mathbf{C} = \{\mathbf{C}_1, \mathbf{C}_2, \cdots, \mathbf{C}_{2^L}\}$ according to (7)
6: Map $\mathbf{C}$ into the solution X_{int}
7: Calculate ZZ_R in (6) by X_{int}
8: **end for**
9: Find the largest $ZZ_R(ZZ_R \ge \alpha ZZ_{opt})$ and its corresponding cluster $\mathbf{C}$
10: **return** $\mathbf{C}$

where θ_k^n is the access factor, which indicates the probability of UE k successfully access to FBS n, which can be formulated as:

$$\theta_k^n = \begin{cases} \frac{L_n^{max} - L_n}{L_n^{max}} & \text{if} \quad L_n < L_n^0 \\ \frac{L_n^{max} - L_n}{L_n^{max}} \cdot \frac{L_n^0}{L_n} & \text{if} \quad L_n \ge L_n^0 \end{cases} \tag{9}$$

where L_n^{max} is the maximum acceptable traffic load of FBS n in a subframe. Aa subframe is divided into two slots: $L_n^0 = L_n^{max}/2$ by Rounding Robin Scheduling. L_n is the current traffic load of FBS n. The expression of EE_k^n is given as follows:

$$EE_k^n = \frac{R_k^n}{P_n} = \frac{B \cdot \log_2(1 + \gamma_k^n)}{P_n} \tag{10}$$

4 Cluster-Based FBSs On/Off Algorithm

Based on the previous analysis, we could obtain the optimal association scheme for UEs and FBSs. To further improve EE, a cluster-based FBSs on/off (CBFOO) algorithm is proposed in this section, which jointly consider the load balancing, the intra-cluster interference and the transmission performance of UEs in the core area. The optimization problem with the load-balancing and the target-SINR threshold constraints can be formulated as:

$$\begin{aligned}
\max_{\lambda,S} \quad & EE = \frac{\sum_{k\in\mathbf{K}}\sum_{n\in\{\mathbf{M},\mathbf{C}\}} B\log 2(1+S_k^n\gamma_k^n)}{\sum_{n\in\{\mathbf{M},\mathbf{C}\}} P(\lambda_n)} \\
\text{s.t.} \quad & \text{C1}: S_k^n \in (0,1), \forall k \in \mathbf{K}, n \in \{\mathbf{M},\mathbf{C}\} \\
& \text{C2}: \sum\nolimits_{n\in\{\mathbf{M},\mathbf{C}\}} S_k^n \le 1, \forall k \in \mathbf{K} \\
& \text{C3}: \sum\nolimits_{k\in\mathbf{K}} S_k^n \le L_n^{max}, \forall n \in \{\mathbf{M},\mathbf{C}\} \\
& \text{C4}: P_{out} \le \rho \\
& \text{C5}: SINR_k^n \ge SINR_k^{th}, \forall k \in \mathbf{K}, n \in \{\mathbf{M},\mathbf{C}\} \\
& \text{C6}: \gamma_k^n = \frac{P_n L(d_{k,n})\lambda_n}{\sum_{n'\in\mathbf{I}\backslash\mathbf{C}_z} P_{n'} L(d_{k,n'})\lambda_{n'} + N_0 B}
\end{aligned} \tag{11}$$

where C1 is the connection indicator of UE k and FBS n or not. C2 indicates that a UE can only associate with one FBS at a time. C3 ensures the load balancing of FBSs. C4 shows the total outage probability of HCNs should not exceed the predetermined threshold. C5 is the target-SINR constraint of UE k. C6 indicates that there is no intra-cell interference, where $\mathbf{C}_z$ is the cluster that UE k belongs to. Therefore, the CBFOO algorithm is described in Algorithm 2.

Algorithm 2 Cluster-Based FBSs on/off (CBFOO) Algorithm

```
Initialization: t = 0, λ = 1, C = {C_1, C_2, ··· , C_Z}, Φ = {EE^{C_1}, EE^{C_2} ··· , EE^{C_Z}}
Associate UEs and BSs by the UFALB algorithm
Generate clusters by algorithm 1 and calculate EE(t) by (11)
for z = 1 : Z do
    Calculate energy efficiency of cluster C_z, EE^{C_z}
end for
repeat
    Find the cluster C_z with the minimum EE, C_z = arg min Φ
    repeat
        Find FBS n of cluster C_z with the minimum EE, n = arg min EE^{C_z}
        if no UEs locate in the core area of FBS n then
            λ_n = 0 and calculate EE(t + 1) by (11)
            if EE(t + 1) ≤ EE(t) or P_out > ρ then
                λ_n = 1
                Break
            end if
            EE(t) = EE(t + 1)
            t = t + 1
        end if
        Delete FBS n from C_z
    until C_z is empty
    Delete EE^{C_z} from Φ
    Delete C_z from C
until C is empty
return λ, EE(t)
```

5 Simulation Results

In this section, we evaluate the performance of the proposed CBFOO algorithm. In the scenario, FBSs and UEs are randomly distributed in the coverage of the MBS. In the simulation, a comparison between the proposed algorithm, the MAX-SINR algorithm, the UE-FBS association load balancing (UFALB) algorithm and the random cluster-based (RCB) algorithm is adopted to evaluate the performance of the proposed algorithm in various aspects. The simulation parameters are shown in Table 1.

Table 1. Simulation parameters

Parameter	Value
Macro base station radius	200 m
MBS transmission power	46 dBm
FBS transmission power	20 dBm
Number of FBSs	25
Maximum acceptable load of a MBS	120
Maximum acceptable load of a FBS	8
Outage probability threshold ρ	0.01
Noise power N_0	–174 dBm/Hz
Maximum size of a cluster	5

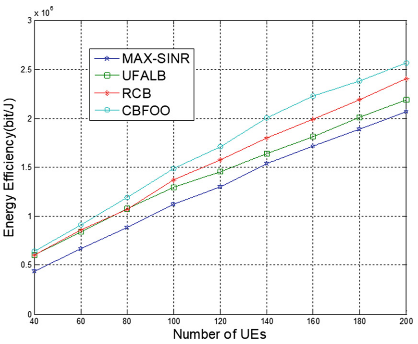

Fig. 2. EE versus number of UEs for different algorithms

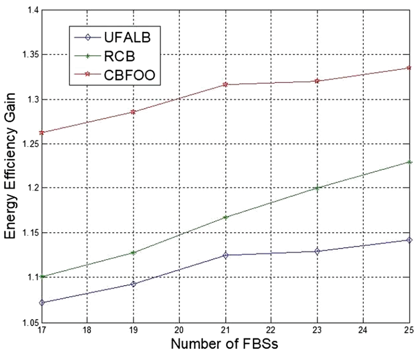

Fig. 3. EE gain versus the number of FBSs for different algorithms

Figure 2 shows that EE of the four algorithms gradually increases with the number of UEs increasing. In the MAX-SINR algorithm, UEs will select FBSs

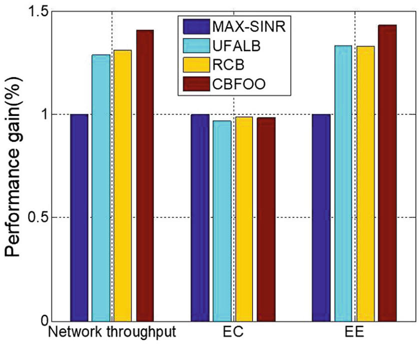

Fig. 4. Performance gain for different algorithms

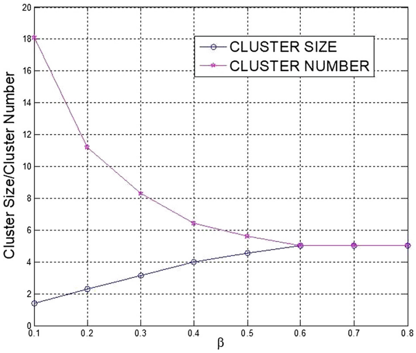

Fig. 5. Impact of β on the cluster size/cluster number

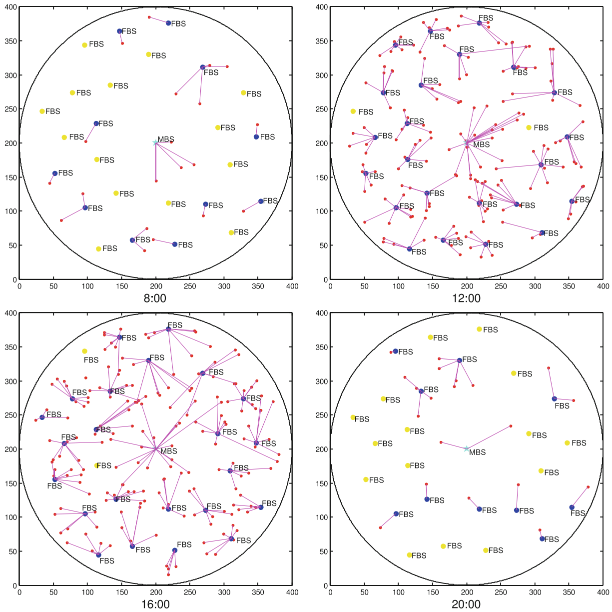

Fig. 6. UE-FBS association and FBSs on/off strategy at time 8:00 a.m, 12:00 a.m, 16:00 p.m, and 20:00 p.m

with the largest received SINR. The UFALB algorithm can choose a suitable association manner between UEs and FBSs, while taking into account the load balancing and the network outage probability. Based on the UFALB algorithm, the RCB algorithm randomly divide FBSs into different clusters. Additionally, the proposed CBFOO algorithm will turn off parts of FBSs based on the current traffic load to further improve EE.

In Fig. 3, compared with the MAX-SINR algorithm, the EE gain of three algorithms significantly raises with the number of FBSs increasing. Moreover, the EE gain of the CBFOO algorithm is higher than the others. On the other hand, the UFALB algorithm is higher than the MAX-SINR algorithm. It shows that the CBFOO algorithm can achieve ultimate goal.

Figure 4 illustrates the performance of network throughput, energy consumption (EC), and energy efficiency (EE) for different algorithms. The MAX-SINR algorithm is the basic algorithm whose performance gains always equal to 1. Since the others algorithms can turn off parts of FBSs, the intra-layer interference is smaller, which could increase the network throughput and reduce the total EC. Furthermore, the CBFOO and RCB algorithm can effectively reduce the intra-cluster interference, increase SINR for UE k, and further improve the throughput compared with the UFALB algorithm. On the other hand, the strict constraints restrain HCNs from turning off more FBSs in the CBFOO and RCB algorithms, thus the network energy consumption in these two algorithms is larger than that in the UFALB algorithm.

In Fig. 5, β represents the weight of w^+, i.e., similarity degree. From (5), we can see that when β is small, there are more clusters in the HCN in order to maximize the object function. As β increasing, the cluster size and the cluster number gradually reach a plateau, because the maximum cluster size M restrains more FBSs join a cluster.

Figure 6 shows the dynamic BS-UE association during a day at time $8:00$ a.m, $12:00$ a.m, $16:00$ p.m, and $20:00$ p.m. respectively. The star represents the MBS, the yellow points indicate the FBS which is turned off, whereas the blue points indicate the FBS which is in full operation mode, and the red points indicate the UE. Mention that if the FBS does connect to any UEs, it will be turned off. One the other hand, the UE is considered outage user when it doesn't connect with a BS. Through this picture, we can observe that FBSs can achieve a load balancing with a large number of UEs while guaranteeing outage probability in HCNs.

6 Conclusion

In this paper, we studied a cluster-based dynamic FBSs on/off scheme to improve EE in HCNs. The proposed cluster-based dynamic FBSs on/off scheme could jointly consider the load balancing, Qos requirement of HCNs, and EE improvement. Specially, the SDP-based Correlation Clustering algorithm with low computational complexity was introduced to obtain good correlation clustering, and the CBFOO algorithms is used to improve EE observably. Our work had significant contributions for future EE research.

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