Collaborative and Green Resource Allocation in 5G HetNet with Renewable Energy

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Abstract. By deploying dense renewable-connected small-cells, heterogeneous networks (HetNets) are able to provide spectral and energy efficiencies for 5G system. However, the small-cell base stations (BSs) may suffer the intra-cell interferences and variabilities of renewable energy. In this paper, we firstly introduce a collaborative architecture to deal with intra-cell interferences and renewable uncertainty for different-tier of users in HetNets. A stochastic optimization problem is formulated to maximize the energy efficiency of collaborative HetNet. To solve the problem, a centralized resources allocation algorithm is proposed based on random variabilities of spectrum and renewable resources. Finally, the extensive numerical results are provided to verify the effectiveness of the proposed collaborative resources allocation method.

Keywords: Collaborative HetNet · Resource allocation
Renewable uncertainty

1 Introduction

Heterogeneous network (HetNet) is treated as a promising solution to support tremendous number of diverse terminals and wireless services in 5G system. However, the dense deployment of small-cell BSs and terminals in HetNet will lead to two important issues: spectrum efficiency and energy efficiency. To address these two issues, some technologies have been intensively studied. Massive multiple-input multiple-output (MIMO) technology have been proven to its potential of significantly improving the spectral efficiency about 10–20 times in the same frequency bandwidth [1]. Cognitive radio (CR) technology has been proposed to effectively utilize the spectrum [2,3]. The CR users/devices are allowed to opportunistically operate in the frequency bands originally allocated to the primary

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users/devices when these bands are not occupied by primary users. Along with the spectral efficiency, energy efficiency also attract intensive research interests. Recent research activities mainly focus on renewable connected BSs and devices, energy efficient communication techniques, energy-driven software defined radio and energy-efficient beamforming technologies for MIMO systems, etc.

To evaluate different spectrum and energy efficient technologies, an unified framework is expected for maximizing the spectrum efficiency while reduce the energy consumption. A widely accepted framework is defining the energy efficiency as the ratio of the transmitted traffic loads to the consumed energy for transmitting such loads [5–9]. Based on this definition, many literatures devoted to maximize the energy efficiency under different wireless network scenarios. In [7], the energy efficiency performance is improved in the heterogeneous cloud radio access network. An energy-efficient optimization problem with the resource assignment and power allocation is formulated to characterize user association with remote radio head or high power node. The authors in [8] propose a resource allocation algorithm to achieve maximum energy efficiency for a given spectrum efficiency for heterogeneous network by using coordinated multi-point transmissions. In [5], four green transmission technologies are introduced to balance the tradeoff between energy and spectrum efficiency for 5G wireless networks. An energy efficient and spectrum efficient wireless heterogeneous network framework for 5G systems is introduced in [6]. The system framework is based on cooperative radios, which aims at balancing and optimizing spectrum and energy efficiency. However, the small-cell base stations (BSs) may suffer the variabilities of renewable resources, which will drastically degrade the coverage and capacity of the heterogeneous networks.

In this paper, we dedicate to investigate the collaborative spectrum and power allocation method of macro-cell Bs and small-cell BSs by maximizing the energy efficiency. Taking into account of the uncertain renewable resources, we formulate a stochastic optimization problem to maximize the energy efficiency for collaborative HetNet. Three key parameters are obtained to characterize the proposed collaborative method: the optimal spectrum assignment of small-cell BSs, the optimal power levels of both small-cell and macro-cell users. To solve the stochastic optimization problem, we reformulate the original nonlinear fractional optimization problem as an equivalent convex feasibility problem. Then, A centralized algorithm based on sample average approximation (SAA) is proposed to solve the stochastic reformulated problem. Finally, the numerical results show the effectiveness of the proposed collaborative resource allocation method.

The remainder of this paper is organized as follows. In Sect. 2, the system model is introduced. The formulation of the stochastic optimization problem is formulated in Sect. 3. Meanwhile, a centralized algorithm based on SAA method is proposed. Section 4 presents the numerical results to assess the performance of the proposed schemes. Finally, the paper is concluded in Sect. 5.

2 System Model

2.1 Network Infrastructure

We consider a heterogeneous network consists of several macro-cells, which is overlaid by N number of small-cells, as shown in Fig. 1. Each macro-cell BS serves C number of user equipments (UEs) while each small-cell BS serves U number of nodes (UEs or devices). The macro-cell BS can be the traditional cellular network BS which has the fixed location and operation. The intra-backhaul (fiber or microwave backhaul) is used to connect the small-cell BSs to the macro-cell BS in each cell-site. In addition, the UEs and devices are uniformly distributed over the coverage areas of macro-cell and small-cell BSs.

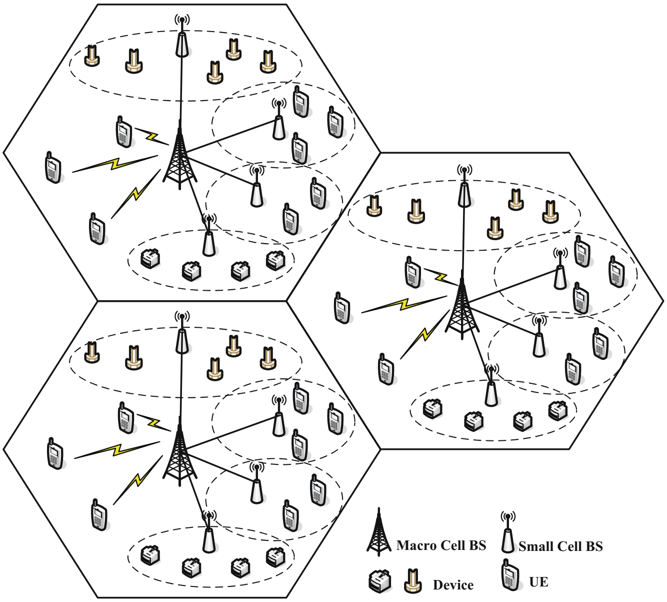

Fig. 1. System model of Hetnet.

2.2 Interference Mitigation Model with Collaboration

Two types of interferences should be carefully considered in Hetnets: Inter-cell interference and Intra-cell interference.

For macro-cell users, the inter-cell interference is coming from other macro BSs in adjacent cells. Meanwhile, the intra-cell interference is also caused by the macro BS transmits signal to other macro-cell users in the same cell. For small-cell users, the inter-cell interference is coming from other macro-cell BSs and small-cell BSs in adjacent cells. Meanwhile, the intra-cell interface is caused by the macro-cell BS and small-cell BSs in the same cell.

To mitigate the inter-cell interferences, collaboration between the macro BSs are critical. Using the backhaul, macro-cell BSs are able to exchange data, control information with each other. Consequently, the inter-cell interferences of macro-cell users and small-cell users can be coordinated. Also, in this paper, we assume that each macro-cell BS has the knowledge of the information of the channel from the BS to its overlaid small-cell users. Then, such channel information is used by macro BS to manage the interference to the small-cell users.

Hence, the signal-to-interference-plus-noise ratio (SINR) for the uth small-cell user in nth small-cell is given by

$$\gamma_{u,n} = \frac{\sigma_{u,n} h_{u,n}}{(P^M \sigma^M_{u,n} h^M_{u,n} + \sum_{m \neq n} p_m \sigma_{m,u,n} h_{m,u,n})} + B_0 N_0 \tag{1}$$

where $\sigma_{u,n}$ and $h_{u,n}$ denote the path loss and the channel gain from the served small-cell BS to the uth small-cell user in nth small-cell, respectively. P^M is the transmit power of macro-BS. $\sigma^M_{u,n}$ and $h^M_{u,n}$ denote the path loss and the channel gain from the macro-cell BS to the uth small-cell user in nth small-cell, respectively. p_m is the transmit power of the mth small BS. $\sigma_{m,u,n}$ and $h_{m,u,n}$ denote the path loss and the channel gain from the mth small cell BS to the uth small-cell user in nth small-cell, respectively. B_0 denote the spectrum of a channel and N_0 denote the estimated power spectrum density (PSD) of both the sum of noise and weak inter-small-cell BS interference (in dBm/Hz).

For macro-cell user, the SINR of cth macro-cell user in kth macro-cell can be obtained as

$$\gamma_{c,k} = \sigma_{c,k} h_{c,k} / B_0 N_M \tag{2}$$

where $\sigma_{c,k}$ and $h_{c,k}$ denote the path loss and the channel gain from the the kth macro-cell BS to the cth macro-cell user, respectively. N_M denote the estimated PSD of the sum of noise.

2.3 Data Rate and Traffic Load Model

Let $R_n(t)$ denote the sum data rate for the nth small-cell BS at time slot t. Then, we have

$$R_n(t) = \sum_{u=1}^{U} B_{u,n}(t) \log_2(1 + \gamma_{u,n} p_{u,n}(t)) \tag{3}$$

where $B_{u,n}(t)$ and $p_{u,n}(t)$ are the spectrum (spectrum resource) and the transmit power allocated to the uth small-cell user in the nth small-cell at time slot t, respectively.

Let $R^M_k(t)$ denote the sum data rate for the kth macro BS at time slot t. Then, we have

$$R^M_k(t) = \sum_{c=1}^{C} B_0 \log_2(1 + \gamma_{c,k} p_{c,k}(t)) \tag{4}$$

where $p_{c,k}$ is the transmit power allocated to the cth macro-cell user in nth small-cell.

Therefore, the sum data rate of the kth macro-cell at time slot t can be written as

$$R_k(t) = \sum_{n=1}^{N} R_n(t) + R_k^M(t). \tag{5}$$

In our model, we assume that the traffic load of each cell-site is different and use random variable $d_n(t)$ to indicate the traffic load of the nth cell-cite at time slot t. Let d_n^{max} denote the maximum value of the traffic load in nth cell-site. We have

$$0 \leq d_n(t) \leq d_n^{max}, \forall n, t. \tag{6}$$

To guarantee the QoS requirement of each cell, we set a minimum threshold for how much traffic load must be served. In this paper, we assume that for the entire time horizon, there is at least $1 - \delta$ probability that the total traffic load will be served. Then, we have the following relationship

$$Pr\big(\sum_{t=0}^{T-1}\sum_{n=1}^{N} d_n(t) - \sum_{t=0}^{T-1}\sum_{n=1}^{N} R_n(t) \leq 0\big) \geq 1 - \delta. \tag{7}$$

2.4 Energy Consumption Model

The total power consumption P_k for kth cell mainly depends on the power consumption of N number of small-cells and the macro-cell BS. The power consumption per small-cell is written

$$P_n(t) = a\sum_{u=1}^{U} p_{u,n}(t) + P_{circuit} + P_{basic} \tag{8}$$

where $p_{u,n}$ is the transmit power allocated to uth small-cell user in nth small-cell. a, P_{cir} and P_{bas} are the efficiency of the power amplifier, circuit power and basic power consumed by small-cell BS, respectively.

The power consumption per macro-cell is written

$$P_k^M = a^M \sum_{c=1}^{C} p_c + P_{circuit}^M + P_{basic}^M \tag{9}$$

where p_c is the transmit power allocated to cth macro-cell user in a macro-cell. a^M, P_{cir}^M and P_{bas}^M are the efficiency of the power amplifier, circuit power and basic power consumed by macro-cell BS, respectively.

Therefore, the total power consumption of kth cell is

$$P_k(t) = \sum_{n=1}^{N} P_n(t) + P_k^M. \tag{10}$$

3 Optimal Resource Allocation for Small-Cells

3.1 Problem Formulation

The energy efficiency is defined as the ratio of the sum data rate and the energy consumption.

$$\Theta(t) = \frac{\sum_{k=1}^{K} R_k(t)}{\sum_{k=1}^{K} P_k(t)} \tag{11}$$

The main objective of this paper is to maximize the energy efficiency by allocating the power and spectrum. In addition, it considers the power and spectrum variabilities of the renewable-connected small-cell BSs. Then, we have the stochastic optimization problem as follows

$$(\mathbf{P1}) \max_{p_{c,k}, B_{u,n}(t), p_{u,n}(t),} \quad \lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} \Theta(t) \tag{12}$$

$$s.t. \quad \sum_{u=1}^{U} p_{u,n}(t)\sigma_{sm}h_{sm} \leq \eta_s, \tag{13}$$

$$\sum_{c=1}^{C} p_{c,k}\sigma_{ms}h_{ms} \leq \eta_m, \tag{14}$$

$$\sum_{c=1}^{C} p_{c,k} \leq P_{k,max}, \tag{15}$$

$$\sum_{u=1}^{U} p_{u,n}(t) \leq \tilde{P}_n(t), \tag{16}$$

$$\sum_{u=1}^{U} B_{u,n}(t) \leq \tilde{B}_n(t), \tag{17}$$

$$Pr\big(\beta \sum_{t=1}^{T}\sum_{n=1}^{N} d_n(t) - \sum_{t=1}^{T}\sum_{n=1}^{N} R_n(t) \leq 0\big) \geq 1-\delta, \tag{18}$$

where η_s and η_m denote the maximum interference that the small-cell BS allows to generate to the macro-cell users and the macro BS allows to generate to the small-cell users, respectively. σ_{sm} and h_{sm} denote the corresponding path loss and channel gain from the small-cell BS to the interfering macro-cell users, respectively. σ_{ms} and h_{ms} denote the corresponding path loss and channel gain from the macro BS to the interfering small-cell users, respectively. $P_{k,max}$ denote the maximum transmit power of the kth macro-cell BS. $\tilde{P}_n(t)$ and $\tilde{B}_n(t)$ denote the maximum transmit power and spectrum can be obtained in the nth renewable connected small-cell BS at time slot t, respectively. Constraint (18) ensures that for the entire time horizon, there is at least $1-\delta$ probability that the served traffic loads is larger than or equal to the minimum level β, $0 < \beta < 100\%$.

3.2 Problem Transformation

The problem (**P1**) is a stochastic problem due to the uncertainty of the transmit power $\tilde{P}_n(t)$, available spectrum $\tilde{B}_n(t)$ and traffic loads $d_n(t)$ of small cell n at time slot t, respectively. In this paper, we use the Sample Average Approximation (SAA) method in which the true distributions of the transmit power, available spectrum and traffic load are replaced by empirical distributions by using the Monte Carlo simulation.

Specifically, to estimate the transmit power $\tilde{P}_n(t)$, the Monte Carlo simulation generates I number of scenarios, each with the same probability $1/I$. After the scenarios are generated, the expected value function of the transmit power can be estimated by the sample average functions as follows:

$$\tilde{P}_n(t) \sim I^{-1} \sum_{i=1}^{I} P_n(t, \varphi_i),$$

where $\varphi_i, i = 1, \cdots, I$, are independent and identically distributed (i.i.d.) samples of I realizations of the transmit power $\tilde{P}_n(t)$. Similarly, the expected value function of the available spectrum $\tilde{B}_n(t)$ and traffic load $d_n(t)$ can be estimated by the sample average functions as follows, respectively:

$$\tilde{B}_n(t) \sim I^{-1} \sum_{i=1}^{I} B_n(t, \omega_i), \quad d_n(t) \sim \frac{1}{I} \sum_{i=1}^{I} d_n(t, \xi_i),$$

where $\{\omega_i, \xi_i, i = 1, \cdots, I\}$ are independent and identically distributed (i.i.d.) samples of I realizations of the available spectrum and traffic load, respectively. Hence, the constraints (16) and (17) can be rewritten as follows:

$$I \sum_{u=1}^{U} p_{u,n}(t) \leq \sum_{i=1}^{I} P_n(t, \varphi_i) \tag{19}$$

$$I \sum_{u=1}^{U} B_{u,n}(t) \leq \sum_{i=1}^{I} B_n(t, \omega_i) \tag{20}$$

Moreover, let $G(\xi_i) \triangleq \beta \sum_{t=0}^{T-1} \sum_{n=1}^{N} d_n(t, \xi_i) - \sum_{t=0}^{T-1} \sum_{n=1}^{N} R_n(t)$. Accordingly, the constraint (18) can be estimated by an indicator function

$$I^{-1} \sum_{i=1}^{I} \mathbf{1}_{(0,\infty)}(G(\xi_i)) \leq \delta \tag{21}$$

where the value of the indicator function $\mathbf{1}_{(0,\infty)}(G(\xi_i))$ is equal to one when $G(\xi_i) \in (0, \infty)$ and zero when $G(\xi_i) \leq 0$.

In addition, the fractional objective function (12) of the optimization problem (**P1**) makes the problem to be a non-linear fractional programming problem. According to [7], the fractional objective can be converted to the subtractive form and the fractional programming problem (**P1**) can be transformed as

$$(\mathbf{P2}) \max_{p_{c,k}, B_{u,n}(t), p_{u,n}(t)} \sum_{k=1}^{K} \bar{R}_k - \Theta^* \sum_{k=1}^{K} \bar{P}_k$$
$$\text{s.t.} \quad (13)-(15), (19)-(21).$$

where $\bar{x} = \lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} x(t)$ and Θ^* is the optimal value of $\bar{\Theta}$. The problem ($\mathbf{P2}$) is equivalent to problem ($\mathbf{P1}$) by the following theorem.

Theorem 1. Θ^* *is an optimal solution for (**P1**) if and only if* Θ^* *is an optimal solution for (**P2**) to satisfy the constraints (13)–(15) and (19)–(21).*

Proof: We prove the Theorem 1 with two steps: sufficient condition proof and necessary condition proof.

(1) Sufficient condition proof: we define $\Theta^* = \frac{\bar{R}(\mathbf{B}^*,\mathbf{p}^*)}{\bar{P}(\mathbf{B}^*,\mathbf{p}^*)}$, where $\mathbf{B}^*$ and $\mathbf{p}^*$ are the optimal spectrum and power allocation policies of the *small-cell users*, respectively. It is easy to obtain the following expression:

$$\Theta^* = \frac{\bar{R}(\mathbf{B}^*, \mathbf{p}^*)}{\bar{P}(\mathbf{B}^*, \mathbf{p}^*)} \geq \frac{\bar{R}(\mathbf{B}, \mathbf{p})}{\bar{P}(\mathbf{B}, \mathbf{p})}, \tag{22}$$

where $\mathbf{B}$ and $\mathbf{p}$ are the feasible spectrum and power results by solving problem ($\mathbf{P1}$). Then, we have

$$\begin{cases} \bar{R}(\mathbf{B}, \mathbf{p}) - \Theta^* \bar{P}(\mathbf{B}, \mathbf{p}) \leq 0 \\ \bar{R}(\mathbf{B}^*, \mathbf{p}^*) - \Theta^* \bar{P}(\mathbf{B}^*, \mathbf{p}^*) = 0 \end{cases}$$

It is obvious that $\max_{\{\mathbf{B},\mathbf{p}\}} \bar{R}(\mathbf{B}, \mathbf{p}) - \Theta^* \bar{P}(\mathbf{B}, \mathbf{p}) = 0$ and the maximum value is obtained by the optimal spectrum and power allocation policies $\mathbf{B}^*$ and $\mathbf{p}^*$. The sufficient condition is proved.

(2) Necessary condition proof: we assume that $\hat{\mathbf{B}}^*$ and $\hat{\mathbf{p}}^*$ are the optimal spectrum and power allocation policies of the objective function of problem ($\mathbf{P2}$), respectively. Then, we can obtain $\bar{R}(\hat{\mathbf{B}}^*, \hat{\mathbf{p}}^*) - \Theta^* \bar{P}(\hat{\mathbf{B}}^*, \hat{\mathbf{p}}^*) = 0$. For any feasible spectrum and power allocation policies $\mathbf{B}$ and $\mathbf{p}$, we have the following expression:

$$\bar{R}(\mathbf{B}, \mathbf{p}) - \Theta^* \bar{P}(\mathbf{B}, \mathbf{p}) \leq \bar{R}(\hat{\mathbf{B}}^*, \hat{\mathbf{p}}^*) - \Theta^* \bar{P}(\hat{\mathbf{B}}^*, \hat{\mathbf{p}}^*) = 0. \tag{23}$$

The above inequality can be derived as:

$$\frac{\bar{R}(\mathbf{B}, \mathbf{p})}{\bar{P}(\mathbf{B}, \mathbf{p})} \leq \Theta^* \quad \text{and} \quad \frac{\bar{R}(\hat{\mathbf{B}}^*, \hat{\mathbf{p}}^*)}{\bar{P}(\hat{\mathbf{B}}^*, \hat{\mathbf{p}}^*)} = \Theta^* \tag{24}$$

Hence, the optimal resource allocation policies $\hat{\mathbf{B}}^*$ and $\hat{\mathbf{p}}^*$ of the objective function of problem ($\mathbf{P2}$) are also the optimal policies of problem ($\mathbf{P1}$). The necessary condition is proved. ■

Based on Theorem 1, the objective function of problem (**P1**) is transformed into the subtractive form in problem (**P2**). In the following subsection, we will propose an iterative algorithm (Algorithm 1) to solve problem (**P2**). In the Algorithm 1, the value of Θ is updated while ensuring the corresponding solution $\{\mathbf{B}, \mathbf{p}\}$ remains feasible in each iteration. The convergence proof is also provided.

3.3 Solution

To solve the problem (**P2**), we first define $F(\Theta) = \max_{\{\mathbf{B},\mathbf{p}\}} \bar{R}(\mathbf{B}, \mathbf{p}) - \Theta \bar{P}(\mathbf{B}, \mathbf{p})$ and have the following Lemma.

Lemma 1. *For all feasible* $\boldsymbol{B}$*,* $\boldsymbol{p}$ *and* Θ*,* $F(\Theta)$ *is a strictly monotonic decreasing function in* Θ *and* $F(\Theta) \geq 0$*.*

Proof: Let Θ_1 and Θ_2 denote the optimal value of the $F(\Theta)$ with optimal solution $\{\mathbf{B}_1, \mathbf{p}_1\}$ and $\{\mathbf{B}_2, \mathbf{p}_2\}$. Assume that $\Theta_1 > \Theta_2$, we have following expression:

$$\begin{aligned} F(\Theta_2) &= \bar{R}(\mathbf{B}_2, \mathbf{p}_2) - \Theta_2 \bar{P}(\mathbf{B}_2, \mathbf{p}_2) \\ &> \bar{R}(\mathbf{B}_1, \mathbf{p}_1) - \Theta_2 \bar{P}(\mathbf{B}_1, \mathbf{p}_1) \\ &> \bar{R}(\mathbf{B}_1, \mathbf{p}_1) - \Theta_1 \bar{P}(\mathbf{B}_1, \mathbf{p}_1) = F(\Theta_1) \end{aligned} \tag{25}$$

Hence, $F(\Theta)$ is a strictly monotonic decreasing function in terms of Θ.

Moreover, let $\mathbf{B}_j$ and $\mathbf{p}_j$ be any feasible spectrum and power allocation policies, respectively. Let $\Theta_j = \frac{\bar{R}(\mathbf{B}_j,\mathbf{p}_j)}{\bar{P}(\mathbf{B}_j,\mathbf{p}_j)}$, then

$$\begin{aligned} F(\Theta_j) &= \max_{\{\mathbf{B},\mathbf{p}\}} \bar{R}(\mathbf{B}, \mathbf{p}) - \Theta_j \bar{P}(\mathbf{B}, \mathbf{p}) \\ &\geq \bar{R}(\mathbf{B}_j, \mathbf{p}_j) - \Theta_j \bar{P}(\mathbf{B}_j, \mathbf{p}_j) = 0. \end{aligned} \tag{26}$$

Therefore, $F(\Theta) \geq 0$. ■

Then, we propose Algorithm 1 to solve problem (**P2**). The proposed algorithm is operated in two steps: initialization and iteration. In initialization step, the initial value of Θ, maximum number of iterations I_{max} and the convergence condition ε are given, respectively. In the iteration step, the optimal problem $F(\Theta_i)$ is solved to achieve the optimal value of $\mathbf{B}_i$ and $\mathbf{p}_i$ with Θ_i. Then, under the convergence condition ε, the value of Θ_{i+1} is updated with the $\bar{R}(\mathbf{B}_i, \mathbf{p}_i)$ and $\bar{P}(\mathbf{B}_i, \mathbf{p}_i)$ obtained in the last iteration. Further, we provide the convergence proof of Algorithm 1 by the following theorem.

Theorem 2. *The Algorithm 1 converges to the global optimal solution of* $F(\Theta)$*.*

Proof: Let Θ_i and Θ_{i+1} denote the energy efficiency of the heterogeneous network in the ith and $(i+1)$th iteration, respectively. Note that in Algorithm 1, Θ_{i+1} is set by $\Theta_{i+1} = \frac{\bar{R}(\mathbf{B}_i,\mathbf{p}_i)}{\bar{P}(\mathbf{B}_i,\mathbf{p}_i)}$. Meanwhile, $F(\Theta) > 0$ as shown in Lemma 1, thus we can obtain

$$\begin{aligned} F(\Theta_i) &= \bar{R}(\mathbf{B}_i, \mathbf{p}_i) - \Theta_i \bar{P}(\mathbf{B}_i, \mathbf{p}_i) \\ &= \bar{P}(\mathbf{B}_i, \mathbf{p}_i)(\Theta_{i+1} - \Theta_i) > 0. \end{aligned} \tag{28}$$

Algorithm 1. Spectrum and Energy Allocation.

Initialization:
1: Set the initial value $\Theta_i = 0$;
2: Give the maximum number of iterations I_{max};
3: Give the convergence condition ε;
Iteration:
4: Let the iteration index $i = 1$;
5: **for** $1 \leq i \leq I_{max}$
6: Solve the following problem

$$F(\Theta_i) = \max_{\{\mathbf{B}_i, \mathbf{p}_i\}} \bar{R}(\mathbf{B}_i, \mathbf{p}_i) - \Theta_i \bar{P}(\mathbf{B}_i, \mathbf{p}_i) \quad \text{s.t.} \quad (13)-(15), (19)-(21); \tag{27}$$

7: Obtain $\mathbf{B}_i, \mathbf{p}_i$, $\bar{R}(\mathbf{B}_i, \mathbf{p}_i)$ and $\bar{P}(\mathbf{B}_i, \mathbf{p}_i)$;
8: **If** $\bar{R}(\mathbf{B}_i, \mathbf{p}_i) - \Theta_i \bar{P}(\mathbf{B}_i, \mathbf{p}_i) < \varepsilon$, **then**
9: Set $\{\mathbf{B}^*, \mathbf{p}^*\} = \{\mathbf{B}_i, \mathbf{p}_i\}$ and $\Theta^* = \Theta_i$;
10: **break**;
11: **else**
12: Calculate $\Theta_{i+1} = \frac{\bar{R}(\mathbf{B}_i, \mathbf{p}_i)}{\bar{P}(\mathbf{B}_i, \mathbf{p}_i)}$ and $i = i + 1$;
13: **end if**
14: **end for**

The above expression indicates that $\Theta_{i+1} > \Theta_i$ due to $\bar{P}(\mathbf{B}_i, \mathbf{p}_i) > 0$, which suggests that Θ increases in each iteration Algorithm 1. Thereby, the Algorithm 1 ensures Θ increases monotonically.

According to the definition of Θ presented in Sect. 2, it is easy to obtain that $\Theta_i > 0$ and $\Theta_{i+1} > 0$ and neither of them is the optimal value Θ^*. Since Θ^* is the maximum energy efficiency for all feasible $\{\mathbf{B}, \mathbf{p}\}$, we have $\Theta^* \geq \Theta_{i+1}$. When the updated Θ increases to Θ^*, we can obtain the value of Θ^* and $F(\Theta^*) = 0$. If the number of iteration in Algorithm 1 is sufficiently large and the optimal conditions as stated in Theorem 1 is satisfied, the problem $F(\Theta)$ converges to zero. Therefore, the global convergence of Algorithm 1 is proved. ■

4 Numerical Results

In this section, numerical simulations are performed to evaluate the performance of the proposed collaborative resource allocation method (denoted by "Proposed Collaborative Method") in a HetNet with renewable penetration. The fixed power allocation method (denoted by Fixed Power Method), is presented as the baseline. In the Fixed Power Method, the same and fixed transmit power is set for different small-cells without considering the uncertainty of renewable, and the optimal spectrum and power allocation derived in our paper is not utilized. The evaluation parameters are listed in Table 1.

Table 1. The simulation parameters

N	10	The number of small-cells
C	20	The number of macro-cell users
U	40	The number of small-cell users
B_0	5 MHz	The bandwidth of a spectrum channel
N_0	1 dBm/Hz	The estimated power spectrum density of noise
P_{cir}/P_{cir}^M	0.1W/10W	The circuit power of small-cell/macro-cell BS
P_{bas}/P_{bas}^M	0.1W/0.2W	The basic power of small-cell/macro-cell BS
a/a^M	2/4	The power amplifer of small-cell/macro-cell BS
$P_{k,max}$	100 W	The maximum transmit power of macro-cell BS
$1-\delta$	1/0.8	The probability of serving load

4.1 Energy Efficiency Comparison

Figure 2 shows the comparison of the energy efficiency of the proposed collaborative method and the fixed power method. The energy efficiency increases with the increment of the value of SINR because higher SINR leads to less power consumption by which the small-cell users can meet with their QoS requirements. It is noted that the proposed collaborative method is able to achieve better energy efficiency than that in the fixed power method. This is because the proposed method schedule the power usage of all small-cell users in collaborative way. Meanwhile, the optimal resource allocation solution in the proposed method guarantees the uncertainty of using renewable power can be greatly reduced.

In Fig. 2, we also compare the energy efficiency under two different QoS requirement cases: $1-\delta=0.8$ and $1-\delta=1$, respectively. The second case

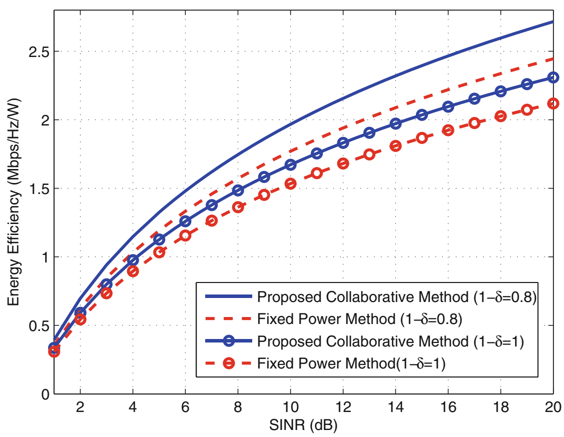

Fig. 2. Energy efficiency comparison in terms of SINR.

indicate that the QoS requirement of each small-cell should be 100% satisfied. It is observed that the energy efficiency in case $1 - \delta = 0.8$ is better than that in case $1 - \delta = 1$. That is, more powers are consumed to make users meet with the QoS requirements.

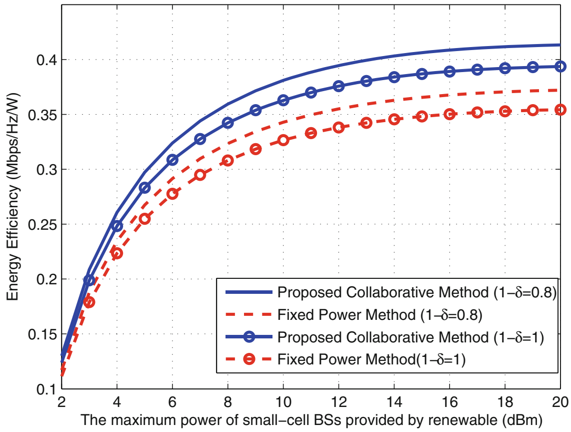

Fig. 3. Energy efficiency comparison in terms of the maximum power of renewable.

Figure 3 shows the energy efficiency comparison between the proposed collaborative method and the fixed power method under different value of the maximum power generated by renewable. In this case, the SINR is set as 1 dB. We can observe that the energy efficiency of the proposed collaborative method is often better than that of the fixed power method. This is because the proposed method can achieve the best energy efficiency performance due to gains of optimal spectrum assignment and power allocation. It is noted that the energy efficiency in the low QoS case $(1 - \delta = 0.8)$ is better than that in the high QoS case $(1 - \delta = 1)$. That is, the power consumption and spectrum requirement in the low QoS case is easy to be satisfied by low level of the power and spectrum allocation.

4.2 Convergence of the Proposed Algorithm

The convergence of both the proposed collaborative method and the fixed power method in term of iteration numbers are illustrated in Fig. 4. The value of SINR of small-cells is set as 1 dB. It can be observed that the plotted energy efficiency of the collaborative method is converged almost within 20 iteration numbers during which the fixed power method is converged. This indicates that the convergence speed is close to the fixed power method which has lower energy efficiency performance.

As shown in simulation results, the proposed collaborative method can achieve better performance than other scheme in HetNet. This is because the

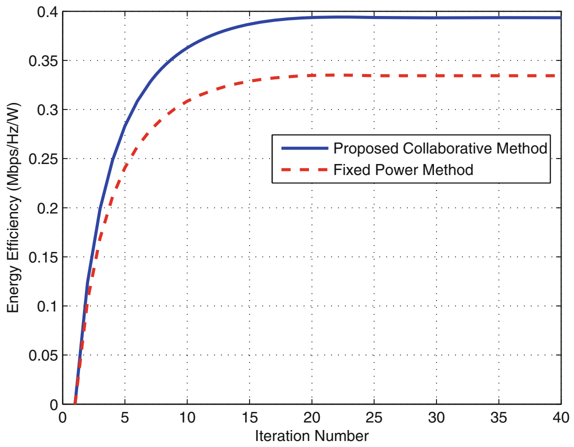

Fig. 4. Convergence of the proposed collaborative method and the fixed power method.

main concern of HetNet is how to provide various applications, by using only one universal device, and satisfy the diverse resources (i.e. spectrum, energy) requirement over multi-tier networks in an optimal way. The proposed collaborative method, imbedded in central controller of the HetNet, collects information of spectrum and renewable resources through the network, intelligently determines current operating settings, and controls the operation of all devices to gain optimal network performance. Hence, the collaborative capability of our method benefits for HetNet.

5 Conclusion

In this paper, we study the energy-efficient resource allocation problem for collaborative macro-cell and small-cell BSs in HetNet with renewable resources. Through stochastic optimization, we develop effective collaborative power and spectrum allocation mechanism for HetNet and show how to optimally schedule the power usage with corresponding allocation mechanism to maximize the energy efficiency. It is expected that this paper provides a collaborative modeling and optimization approach to effectively integrating renewable resource into HetNet.

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References

1. Metis, "Scenarios, requirements and KPIs for 5G mobile and wireless system," ICT-317669 METIS project, May 2013
2. Liu, Y.: A parallel cooperative spectrum sensing in cognitive radio networks. IEEE Trans. Veh. Technol. **59**(8), 4079–4092 (2010)
3. Liu, Y.: SD-MAC: spectrum database-driven MAC protocol for cognitive machine-to-machine networks. IEEE Trans. Veh. Technol. **66**(2), 1456–1467 (2017)
4. Cao, W.: Cellular offloading in heterogeneous mobile networks with D2D communication assistance. IEEE Trans. Veh. Technol. **66**(5), 4245–4255 (2017)
5. Wu, Y.: Green transmission technologies for balancing the energy efficiency and spectrum efficiency trade-off. IEEE Commun. Mag. **52**(11), 112–120 (2014)
6. Hu, R., Qian, Y.: An energy efficient and spectrum efficient wireless heterogeneous network framework for 5G systems. IEEE Commun. Mag. **52**(5), 94–101 (2014)
7. Peng, M.: Energy-efficient resource assignment and power allocation in heterogeneous cloud radio access networks. IEEE Trans. Veh. Technol. **52**(5), 5275–5287 (2015)
8. Huq, K.M.S., et al.: Green HetNet CoMP: energy efficiency analysis and optimization. IEEE Trans. Veh. Technol. **64**(10), 4670–4683 (2015)
9. Liu, C.-H., Fong, K.L.: Fundamentals of the downlink green coverage and energy efficiency in heterogeneous networks. IEEE J. Sel. Areas Commun. **34**(12), 3271–3287 (2016)