Energy-Efficient Resource Allocation in Macrocell-Smallcell Heterogeneous Networks

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Abstract — Cellular users in indoor environments have difficulty to enjoy high rate services from Macro Base Station (MBS) due to the penetration loss. Smallcell, as a complement to Macrocell, can enhance the coverage by constituting heterogeneous network (HetNet). HetNet has been investigated as a promising technique and is considered as a candidate for green communications. However, interference in HetNet is an emergency issue. In this paper, an energy-efficient subchannel and power allocation scheme for a downlink of Macrocell-Smallcell HetNet is proposed. The resource allocation problem to maximize the Energy Efficiency (EE) for all Smallcell Base Stations (SBSs) is formulated as a non-convex optimization problem with the condition of the guaranteed data rate and the cross-tier interference constraint. The problem is transformed into an equivalent form which can be solved by an iterative algorithm. The dual decomposition method is utilized in each iteration to obtain the closed-form solution for the optimal power and resource block allocation. Simulation results show that the proposed EEmax algorithm outperforms the resource allocation algorithm of total capacity maximization in the performance of energy-efficient with a bit of little cost of spectrum efficiency.

Index Terms—Convex optimization, energy efficiency, resource allocation, smallcell

I. INTRODUCTION

In a cellular network, more than 60% of voice services and more than 90% of data traffic take place indoor [1]. Therefore, it is increasingly important to provide better indoor coverage for voice, video and other high-speed data services for cellular network operator. Therefore, Smallcell, which can be used to provide indoor wireless network coverage, is becoming more and more widely used in daily life. Smallcell has a low coverage, which can greatly decrease the distance between user and base station. Therefore, the transmission power of user can be greatly reduced and the service life of mobile terminal can be increased. Smallcells act as a complement to the traditional base stations (called Macrocell) in cellular systems are becoming a hot research issue in the operator and academic field by constituting heterogeneous network (HetNet).

Due to the scarcity of spectrum and the difficulty of actualize, spectrum sharing between Smallcell and Macrocell is more reasonable than spectrum division [2]. In a spectrum sharing network, cross-tier interference between the Smallcell and the Macrocell is an emergency and open issue, and it will seriously affect energy efficiency. Therefore, improving the energy efficiency through resource allocation algorithm in the two-tier network is a meaningful and challenging research issue.

Power allocation has been widely used to maximize user’s capacity while alleviating cross-tier interference in two-tier networks. In [3] power control is utilized to ensure adequate SINR for indoor cell edge user. In [4] a Stackelberg game based power control is formulated to maximize Smallcells’ capacity. A distributed resource allocation scheme based on a potential game and convex optimization is proposed in [5] to increase the total capacity of macrocells and femtocells. Reference [6] applies the dual decomposition method to solve the sum-data-rate maximization problem in multi-user Orthogonal Frequency Division Multiple Access (OFDMA) system. An energy-efficient resource assignment and power allocation in heterogeneous cloud radio access networks with Lagrange dual decomposition method is proposed in [7]. Authors in [8] propose the energy-efficient resource allocation with the consideration on QoS and backhaul link constraints in multi-cell scenario. In [9] a Lagrangian dual decomposition based on power allocation scheme is proposed with cross-tier interference mitigation. On the other hand, channel allocation is applied to suppress the cross-tier interference. However, few works on the energy-efficient resource allocation in HetNet with the consideration on the cross-tier interference have been studied.

In this paper, we focus on an energy-efficient subchannel and power allocation scheme for a downlink of HetNet. It shows that the proposed algorithm outperforms the other algorithms in terms of the energy efficiency. The main contributions of the paper are summarized as follows: 1) In the scenario of HetNet, an energy efficiency model for all Smallcell Base Stations (SBSs) is formulated as a non-convex optimization EEmax problem with the condition of the guaranteed data rate and the cross-tier interference constraint.

2) To solve the proposed non-convex EEmax problem, the original optimized model is divided into fractional...
nonlinear programming and transformed into an equivalent form which can be solved by iterative algorithm.

3) The closed-form expression of the optimal power and resource block allocation problem is derived for each iteration with the Lagrangian dual decomposition method.

4) The efficiency of the proposed EEmax algorithm is verified by simulations, and the cost of EE improvement is a little bit of spectrum efficiency.

The rest of this paper is organized as follows. Section II introduces the system model and formulates the resource allocation problem. In Section III, the non-convex problem is trans- formed into an equivalent optimization problem. By utilizing the dual decomposition method in each iteration, the transformed EE maximization problem is solved by an iterative algorithm. In Section IV, performance of the proposed algorithm is evaluated by simulations. And finally concluding remarks regarding of the proposed algorithm appear in Section V.

II. SYSTEM MODEL AND PROBLEM FORMULATION

The system model is as shown in Fig. 1. In this system model, we consider a single-cell downlink double layers network, which contains a Macro Base Station (MBS) and several macro users (MUES). M Smallcell Base Stations (SBSs) are randomly distributed in the macrocell. Each smallcell base station has N randomly distributed smallcell users (SUES). The considered MUES are located near SBS but far from the serving MBS. Thus, the cross-tier interference from SBS to these MUES must be limited for maintaining the quality of service. As the coverage of each smallcell is usually not overlapped, transmission power is low, and the transmission loss is large. The common channel interference between smallcells is assumed to be part of the thermal noise. The bandwidth of each resource block is B0. The channel gain model is independent and identically distributed Rayleigh fading.

Smallcells’ whole throughput is:

\[ C(a, p) = \sum_{m=1}^{M} R_{m}^S \]

where \( R_{m}^S \) indicates the data rate of \( m \)-th SBS.

\[ R_{m}^S = \sum_{n=1}^{N} \sum_{k=1}^{K} a_{m,n,k} B_0 \log_2 \left( 1 + \text{SINR} \right) \]

where \( a_{m,n,k} = (0, 1) \), indicates whether or not the \( k \)-th RB is assigned to the \( n \)-th SUE in the \( m \)-th SBS.

\[ \text{SINR} = \frac{P_{m,n,k} h_{m,n,k}^{S2S}}{P_m^{M} h_{m,n,k}^{M2S} + N_0 B_0} \]

where \( d_{m,n,k} = h_{m,n,k}^{S2S} / (P_m^{M} h_{m,n,k}^{M2S} + N_0 B_0) \) Therefore, we have

\[ R_{m} = \sum_{n=1}^{N} \sum_{k=1}^{K} a_{m,n,k} B_0 \log_2 \left( 1 + d_{m,n,k} P_{m,n,k} \right) \]

where \( P_{m,n,k} \) expresses the transmit power of the \( m \)-th SBS allocated to the \( n \)-th SUE on the \( k \)-th RB; \( P_m^{M} \) denotes the transmit power of the MBS; \( h_{m,n,k}^{S2S} \) is the channel gain from the \( m \)-th SBS to the \( n \)-th SUE on the \( k \)-th RB; \( h_{m,n,k}^{M2S} \) indicates the channel gain from the MBS to the \( n \)-th SUE on the \( k \)-th RB in the \( m \)-th SBS; \( N_0 \) expresses the noise power spectrum density.

The total power consumption \( P(a, p) \) is mainly related to the transmit power and circuit power. The total power consumption can be obtained by

\[ P(a, p) = \sum_{m=1}^{M} P_m^S \]

where \( P_m^S \) represents the power consumption of the \( m \)-th SBS.

\[ P_m^S = \sum_{n=1}^{N} \sum_{k=1}^{K} a_{m,n,k} P_{m,n,k} + P_c \]

where \( P_c \) is circuit power consumption.

Therefore, the energy-efficiency of reference smallcell is defined as the ratio of the sum of throughput to the total power consumption, of which the unit is bps/W. The optimization problem is performed under the following constraints.

Total power constraint:

\[ \sum_{n=1}^{N} \sum_{k=1}^{K} a_{m,n,k} P_{m,n,k} \leq p_{\text{max}}^S \quad \forall m \]

where \( p_{\text{max}}^S \) denotes total transmit power constraint of the SBS.

The data rate requirement \( \eta_0 \) should be guaranteed for smallcell users to maintain their performance, which requires the following constraint

\[ \sum_{k=1}^{K} a_{m,n,k} B_0 \log_2 \left( 1 + d_{m,n,k} P_{m,n,k} \right) > \eta_0 \quad \forall n, \forall m \]

Set the interference threshold in order to control cross-tier interference from SBS to the MUE which is nearest to SBS in the macrocell.
The optimal value of EE, defined as the following equivalent form:

\[
\max C(a, p) - \gamma P(a, p) \quad \text{(11)}
\]

s.t: C1, C2, C3, C4

where \( \gamma \) is defined as a positive variable indicating the EE.

The optimal value of EE, defined as \( \gamma^* = \frac{C(a^*, p^*)}{P(a^*, p^*)} \), is achieved if and only if

\[
\max_C C(a, p) - \gamma P(a, p) = C(a^*, p^*) - \gamma P(a^*, p^*) = 0 \quad \text{(12)}
\]

Such equivalence has been proved in some works in [7], [8]. By this theorem, for any optimization problem with an objective function in fractional form, there exists an equivalent objective function in subtractive form.

\[
F(\gamma) = \max_C C(a, p) - \gamma P(a, p) \quad \text{(13)}
\]

where the Eq. (12) is equivalent to find the root of the nonlinear equation \( F(\gamma) = 0 \).

Due to the integer variable \( a_{m,n,k} \), the feasible domain of \( a \) is a discrete and finite set consisting of all possible RB allocation schemes. Thus, \( F(\gamma) \) is generally a continuous but non-differentiable function with respect to \( \gamma \). Besides, it is clear that \( F(\gamma) \) is a convex and strictly decreasing function with respect to \( \gamma \). It is obvious that \( \gamma \rightarrow -\infty \) yields \( F(\gamma) > 0 \) and \( F(\gamma) < 0 \) with \( \gamma \rightarrow \infty \). It can be shown that \( F(\gamma) \) will converge to zero when the number of iteration is large enough.

B. Lagrange-Dual-Method-Based Resource Allocation

Solve the non-convex problem by Lagrange dual decomposition method. The dual optimization problem is as follows:

\[
\min \{g(u_{m,n,k}, v_m) \mid u_{m,n} > 0, v_m > 0\} \quad \text{(14)}
\]

s.t: \( u_{m,n} > 0 \quad \forall n \forall m \)

\[
\lambda_k > 0 \quad \forall k \quad \text{(15)}
\]

where \( u_{m,n} \), \( \lambda_k \) and \( v_m \) are the dual variables for the constraints C2, C3 and C4, respectively. Assuming the \( k \)-th RB in the \( m \)-th SBS is assigned to \( n \)-th user, then \( a_{m,n,k} = 1 \).

Right now:

\[
g(u_{m,n}, \lambda_k, v_m) = \max_{(u_{m,n}, \lambda_k, v_m)} L(P_{m,n,k}u_{m,n}, \lambda_k, v_m) \quad \text{(16)}
\]

where \( L(P_{m,n,k}u_{m,n}, \lambda_k, v_m) \) expresses the Lagrange function of the original problem with constraint conditions C2, C3 and C4.

In addition, through literature [12] the dual optimization problem often is convex, and the dual gap is almost 0 when the number of resources is sufficient for the primal problem and dual problem. Therefore, the dual function is decomposed into K independent optimization problems, which can be given by

\[
g_k(u_{m,n}, \lambda_k, v_m) = \max_{(u_{m,n}, \lambda_k, v_m)} \sum_{\forall m} \sum_{\forall k} u_{m,n} B_{m,n,k} \log_2 (1 + d_{m,n,k}P_{m,n,k})
\]

\[
- \gamma \sum_{\forall m} \sum_{\forall k} P_{m,n,k} - v_m \sum_{\forall k} P_{m,n,k}
\]

\[
- \lambda_k \sum_{\forall m} \sum_{\forall k} P_{m,n,k} h_{m,n,k} \quad \text{(16)}
\]
It is obvious that the above function is convex in $P_{m,n,k}$. With using the KKT condition, the optimal power allocation is derived by

$$P_{m,n,k}^* = \left[ \frac{1 + u_{m,n}}{ \ln 2 \left( y + v_m + \lambda_b \delta_{m,n,k}^2 \right)} \right]^+$$

(17)

where

$$(1 + u_{m,n}) B_i / \ln 2 \left( y + v_m + \lambda_b \delta_{m,n,k}^2 \right) = y_{m,n,k}^*.$$

Therefore, we have

$$P_{m,n,k}^* = \left[ \frac{y_{m,n,k}^* - \lambda_b \delta_{m,n,k}^2}{1} \right]^+$$

(18)

We compare all the SUES allocations of the $k$-th RB, bring $P_{m,n,k}^*$ in $g_k (u_{m,n}, \lambda_b, v_m)$, the optimal RB allocation indicator for the given dual variables can be obtained by

$$d_{m,n,k}^* = \begin{cases} n & \text{arg max}_{n \in \mathbb{N}} H_{m,n,k} \\ 0 & \text{otherwise} \end{cases}$$

(19)

where

$$H_{m,n,k} = \left[ \frac{(1 + u_{m,n}) \log_2 \left( y_{m,n,k}^* d_{m,n,k}^* \right)}{1 - \frac{1}{y_{m,n,k}^* d_{m,n,k}^*}} \right] - \frac{(1 + u_{m,n})}{\ln 2} \left[ 1 - \frac{1}{y_{m,n,k}^* d_{m,n,k}^*} \right].$$

In this paper, an iterative algorithm for energy-efficient resource allocation is proposed to solve the transformed problem (11).

C. Iterative Process Based on Lagrange Dual Method

Algorithm Energy-Efficient Resource Allocation

1) Set the maximum number of iterations $I_{\text{max}}$, convergence condition $\xi$, and the initial value $\gamma(0)$.
2) Set the iteration index $i = 1$ and begin the iteration.
3) for $1 \leq i \leq I_{\text{max}}$
4) Solve the resource allocation with $\gamma(i)$;
5) Obtain $a^{(i)}$, $p^{(i)}$, $C(a^{(i)}, p^{(i)})$, $P(a^{(i)}, p^{(i)})$;
6) if $C(a^{(i)}, p^{(i)}) - \gamma(i) PP(a^{(i)}, p^{(i)}) < \xi$, then
7) Set $\{a^*, p^*\} = \{a^{(i)}, p^{(i)}\}$ and $\gamma^* = \gamma(i)$;
8) break;
9) else
10) Set $\gamma^{(i+1)} = C(a^{(i)}, p^{(i)}) / P(a^{(i)}, p^{(i)})$ and $i = i + 1$;
11) end if
12) end for

At the time of the iterative algorithm, the update equation of the Lagrange factor at the $l + 1$th iteration is as follows:

$$u_{m,n}^{l+1} = \left[ u_{m,n}^l - \frac{\partial u_{m,n}^l}{\partial \gamma^l} \times \nabla u_{m,n}^{l+1} \right]^+ \forall m, \forall n$$

(20)

$$\lambda_{k}^{l+1} = \left[ \lambda_{k}^l - \frac{\partial \lambda_{k}^l}{\partial \alpha^l} \times \nabla \lambda_{k}^{l+1} \right]^+ \forall k$$

(21)

where $\nabla u_{m,n}^{l+1}$ and $\nabla \lambda_{k}^{l+1}$ denote the gradient utilized in the $l + 1$th iteration. $\gamma^l$ and $\alpha^l$ are the positive step sizes. Among them, the expression of the Lagrange factor gradient is as follows:

$$\nabla \gamma_{m,n}^{l+1} = \frac{d_m^l}{\frac{1}{\gamma} \left[ \frac{d_n^l}{\gamma} \right]^+}$$

(23)

$$\nabla \alpha_k^{l+1} = \frac{d_k^l}{\frac{1}{\alpha} \left[ \frac{d_k^l}{\alpha} \right]^+}$$

(24)

$$\nabla \lambda_{k}^{l+1} = P_{m,n}^l - \frac{d_{m,n,k}^l}{\lambda_{m,n,k}^l \left[ \frac{d_{m,n,k}^l}{\lambda_{m,n,k}^l} \right]^+} \forall m$$

(25)

where $d_{m,n,k}^l$ and $p_{m,n}^l$ represent the RB allocation and power allocation derived by the dual variables of the $l$-th iteration.

Therefore, the power and resource block for maximize EE can be obtained by the above algorithm, called EEmax.

IV. SIMULATION RESULTS AND DISCUSSION

Simulation results are given in this section to evaluate the performance of the proposed energy-efficient resource allocation algorithm. In the simulations, spectrum-sharing Small-cells are randomly distributed in the macrocell coverage area, and smallcell users are randomly distributed in the coverage area of their serving smallcells. The simulation parameters are shown in Table I.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Macro cell radius</td>
<td>500m</td>
</tr>
<tr>
<td>Macro user number</td>
<td>20</td>
</tr>
<tr>
<td>Distance between MBS and MUE</td>
<td>Rand(0,500)</td>
</tr>
<tr>
<td>Small cell radius</td>
<td>30m</td>
</tr>
<tr>
<td>SUE number in each small cell</td>
<td>5</td>
</tr>
<tr>
<td>Distance between SBS and SUE</td>
<td>Rand(0,500)</td>
</tr>
<tr>
<td>Distance between SBS and MUE</td>
<td>Rand(60,120)</td>
</tr>
<tr>
<td>Distance between MBS and SUE</td>
<td>Rand(350,420)</td>
</tr>
<tr>
<td>Noise power spectral density $N_0$</td>
<td>-174dBm/Hz</td>
</tr>
<tr>
<td>MBS transmission power $P_M^d$</td>
<td>45dBm</td>
</tr>
<tr>
<td>System bandwidth $B_0$</td>
<td>4MHz</td>
</tr>
<tr>
<td>Resource block number $K$</td>
<td>20</td>
</tr>
<tr>
<td>Circuit power consumption $P_c$</td>
<td>20dBm</td>
</tr>
<tr>
<td>SUE data probability requirement $\eta_0$</td>
<td>60Kbps</td>
</tr>
<tr>
<td>Path loss model SBS-to-MUE</td>
<td>31.5+35.0* $\log_{10}(d)$</td>
</tr>
<tr>
<td>Path loss model MBS-to-SUE</td>
<td>31.5+40.0* $\log_{10}(d)$</td>
</tr>
</tbody>
</table>

Fig. 2 shows that the energy efficiency in different algorithms with different number of smallcell users per smallcell. We see that the energy efficiency based on our proposed EEmax algorithm always outperforms the performance of SDmax algorithm. We can also find that, the more the number of users in a smallcell, the better the
performance can be obtained. This is because, as the number of the total subchannels in each smallcell is fixed, with the increase of the number of smallcell users in each smallcell, each subchannel has more candidate smallcell users to select. Therefore, higher energy efficiency can be obtained.

From Fig. 4 we can see that the iterative algorithm can converge to the optimal energy efficiency after 5 iterations. We can also see that when the maximum transmission power is low, the energy efficiency we can achieve after several iterations is relatively low. At this moment the power consumption is mainly consumed in the circuit. With increase of the transmission power, energy efficiency is improved.

From Fig. 5 we can see that when MUE’s SINR threshold is low, SBS can have larger transmission power. The energy efficiency can reach its peak value after several iterations. When MUE’s required SINR is higher, the interference constraints will restrict the transmit power of SBS in order to maintain the MUE’s required SINR. At present, the energy efficiency of smallcells is shown in the picture below.

From Fig. 7 we see that the spectrum efficiency based on SDmax algorithm always outperforms the performance of EEmax algorithm. That is because the EEmax algorithm

Fig. 2. The energy efficiency in different algorithm with different number of smallcell users per smallcell.

Fig. 3 shows the energy efficiency in different algorithms with different MUE-SINR thresholds. We can see that algorithm EEmax outperforms algorithm SDmax in terms of energy efficiency. It can also be seen from the figure that energy efficiency decreases with increase in MUE-SINR threshold. This is because the interference constraints restrict the transmit power of SBS in order to maintain the MUE’s required SINR.

Fig. 4. Energy efficiency (bps/W) versus number of iterations with different maximum transmit power of each SBS.

From Fig. 5 we can see that when MUE’s SINR threshold is low, SBS can have larger transmission power. The energy efficiency can reach its peak value after several iterations. When MUE’s required SINR is higher, the interference constraints will restrict the transmit power of SBS in order to maintain the MUE’s required SINR. At present, the energy efficiency of smallcells is shown in the picture below.

Fig. 6 shows that the energy efficiency of the total throughput for SD maximum resource allocation algorithm improves with the increase of the transmission power, but lower than the energy efficiency of the maximum resource allocation algorithm. On the other hand, the energy efficiency of the maximum resource allocation algorithm can reach its peak value with the increase of transmission power.

Fig. 7 shows that the spectrum efficiency based on SDmax algorithm always outperforms the performance of EEmax algorithm. That is because the EEmax algorithm
mainly considers maximum energy efficiency through reasonably allocating the resource and power. Therefore, the EEmax algorithm has some loss in the spectrum efficiency. However, it is acceptable when considering the enhancement in energy efficiency.

V. CONCLUSIONS

In a spectrum sharing network, cross-tier interference between the smallcell and the macrocell is an emergency issue and it will seriously affect energy efficiency. Improving the energy efficiency through resource allocation algorithm in the two-tier network is meaningful. In this paper, we focus on subchannel and power allocation scheme for a downlink of macrocell-smallcell Heterogeneous Network to maximize the energy efficiency. With the condition of the guaranteed data rate and the cross-tier interference constraint, the subchannel and power allocation problem to maximize the energy efficiency for all SBSs is formulated as a non-convex optimization problem. In order to solve the proposed non-convex problem, we transformed it into an equivalent form of fractional nonlinear programming which can be solved by an iterative algorithm. Simulation results show that the proposed EEmax algorithm outperforms the other algorithms in terms of the energy efficiency. The energy efficiency resource allocation with advanced cross-tier interference management in HetNet will be a hot research direction in the future.

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