Energy-Efficient Resource Allocation in Macrocell-Smallcell Heterogeneous Networks

Lingyun Feng, Yueyun Chen, and Xinzhe Wang
School of Computer & Communication Engineering, University of Science and Technology Beijing, Beijing 100083, China
Email: {13070106360, 17801002625}@163.com; chenyy@ustb.edu.cn

Abstract —Cellular users in indoor environments have difficulty to enjoy high rate services supplied only by macro base station (MBS) due to the penetration loss. Smallcell, as a complement to Macrocell, provide the enhanced coverage through constituting heterogeneous network (HetNet) with MSBs. HetNet is an effective candidate for green communications. However, the interference in HetNet is still a challenging issue. In this paper, we propose an energy-efficient subchannel and power allocation scheme (called EEmax) for a downlink of Macrocell-Smallcell HetNet. The resource allocation to maximize the Energy Efficiency (EE) for all Smallcell Base Stations (SBSs) is formulated a non-convex optimization problem with the condition of the guaranteed data rate and the cross-tier interference constraint. Through an equivalent transformation, an iterative algorithm and the closed-form solution for the optimal power and resource block allocation are obtained. Simulation results show that the proposed EEmax algorithm ballance the resource efficiency both energy and 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 Marcocell) 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 [3]-[11]. In [3] power control is utilized to ensure satisfying SINR for indoor cell edge user. In [4] a Stackelberg game based power control is formulated to maximize Smallcells' capacity. A Bargaining Cooperative Game (BCG) framework for interference-aware power coordination and a minimized power consumption in HetNets is serperately proposed in [5] and [6]. A distributed resource allocation scheme based on a potential game and convex optimization is proposed in [7] to increase the total capacity of macrocells and femtocells. Reference [8] 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 [9]. Authors in [10] propose the energy-efficient resource allocation with the consideration on QoS and backhaul link constraints in multi-cell scenario. In [11] 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. Reference [12] proposes a downlink scheme of the inter-layer interference between macrocells and picocells applying CRE (Cell Range Extension) technique to coordinate frequency and power resource. However, few works are considered focusing on energy-efficiency issue in resource allocation for a HetNet with consideration of the cross-tier interference.

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:

Manuscript received November 1, 2015; revised May 14, 2016.
This work was supported by the National Natural Science Foundation of China under Grant No. 61272506.
Corresponding author email: chenyy@ustb.edu.cn
doi:10.12720/jcm.11.5.440-445

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 transformed 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.

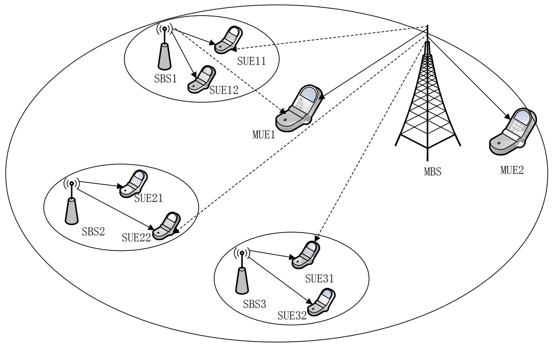

Fig. 1. System model of the two-tier network

Smallcells' whole throughput is:

$$C(a,p)=\sum_{m=1}^{M} R_m^S \tag{1}$$

where R_m^S indicates the data rate of m-th SBS.

$$R_m^S=\sum_{n=1}^{N}\sum_{k=1}^{K} a_{m,n,k} B_0 Log_2\left(1+SINR\right) \tag{2}$$

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.

$$\begin{aligned} SINR &= \frac{P_{m,n,k} h_{m.n.k}^{S2S}}{P^M h_{m,n,k}^{M2S}+N_0 B_0} \\ &= d_{m,n,k} P_{m,n,k} \end{aligned} \tag{3}$$

where $d_{m,n,k}=h_{m,n,k}^{S2S} \big/ \left(P^M h_{m,n,k}^{M2S}+N_0 B_0\right)$. Therefore, we have

$$R_m^S=\sum_{n=1}^{N}\sum_{k=1}^{K} a_{m,n,k} B_0 Log_2\left(1+d_{m,n,k}P_{m,n,k}\right) \tag{4}$$

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 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

$$P(a,p)=\sum_{m=1}^{M} P_m^S \tag{5}$$

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

$$P_m^S=\sum_{n=1}^{N}\sum_{k=1}^{K} a_{m,n,k} P_{m,n,k}+P_c^S \tag{6}$$

where P_c^S 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:

$$\sum_{n=1}^{N}\sum_{k=1}^{K} a_{m,n,k} P_{m,n,k} \le P_{\max}^S \qquad P_{m,n,k}\ge 0 \qquad \forall m \tag{7}$$

where $P_{\max}^S$ denotes total transmit power constraint of the SBS. The data rate requirement η_0 should be guaranteed for smallcell users to maintain their performance, which requires the following constraint:

$$\sum_{k=1}^{K} a_{m,n,k} B_0 Log_2\left(1+d_{m,n,k}P_{m,n,k}\right) > \eta_0 \quad \forall \text{n}, \forall \text{m} \tag{8}$$

Set the interference threshold in order to control cross-tier interference from SBS to the MUE which is nearest to SBS in the marcocell.

$$\sum_{m=1}^{M}\sum_{n=1}^{N} a_{m,n,k} P_{m,n,k} h_{m,n,k}^{S2M} \le \delta_0 \quad \forall k \tag{9}$$

Our target is to maximize the energy-efficiency of SBS under the cross-tier interference constraint and smallcell users' data rate constraint. The corresponding problem can be formulated as the following non-convex optimization problem:

$$\max \eta = \frac{C(a,p)}{P(a,p)} = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{k=1}^{K} a_{m,n,k} B_0 Log_2\left(1+d_{m,n,k}P_{m,n,k}\right)}{\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{k=1}^{K} a_{m,n,k} P_{m,n,k} + MP_c^S} \tag{10}$$

$$\begin{aligned}
s.t.\, C1 \quad & \sum_{n=1}^{N} a_{m,n,k} = 1 \quad \forall k, \forall m \\
C2 \quad & \sum_{k=1}^{K} a_{m,n,k} B_0 Log_2\left(1+d_{m,n,k}P_{m,n,k}\right) > \eta_0 \quad \forall n, \forall m \\
C3 \quad & \sum_{m=1}^{M}\sum_{n=1}^{N} a_{m,n,k} P_{m,n,k} h_{m,n,k}^{S2M} \le \delta_0 \quad \forall k \\
C4 \quad & \sum_{n=1}^{N}\sum_{k=1}^{K} a_{m,n,k} P_{m,n,k} \le P_{\max}^S \quad P_{m,n,k} \ge 0 \ \forall m
\end{aligned}$$

The constraint condition C1 indicates the RB allocation limit, which can only be assigned to at most one smallcell user at a time. C2 indicates the minimum data rate requirements for each SUE. C3 sets the interference threshold in order to control cross-tier interference from macro users close enough to the smallcell. δ_0 represents a cross-tier interference threshold, which is derived from the distance between MBS and MUE and the requirements of the SINR. C4 represents the total transmission power constraint of the SBS.

Because the proposed optimization problem (10) is non-convex, it's difficult to solve directly it. Implied by [13] and [14], we transform the primal problem into an equivalent problem to solve the problem (10) in Section III.

III. Subchannel and Power Allocation Algorithm EEmax

A. Problem Equivalence

The original problem in (10) can be transformed into the following equivalent form:

$$\begin{aligned}
&\max_{(a,p)} \ C(a,p) - \gamma P(a,p) \\
&s.t. \qquad C1, C2, C3, C4
\end{aligned} \tag{11}$$

where γ 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

$$\begin{aligned}
&\max_{(a,p)} C(a,p) - \gamma^* P(a,p) \\
&= C(a^*,p^*) - \gamma^* P(a^*,p^*) = 0
\end{aligned} \tag{12}$$

Such equivalence has been proved [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:

$$F(\gamma) = \max_{(a,p)} C(a,p) - \gamma P(a,p) \tag{13}$$

where the (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 γ. Besides, it is clear that $F(\gamma)$ is a convex and strictly decreasing function with respect to γ. It is obvious that $\gamma \to -\infty$ yields $F(\gamma) > 0$ and $F(\gamma) < 0$ with $\gamma \to \infty$. 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:

$$\begin{aligned}
\min_{\{u_{m,n},\lambda_k,v_m\}} \quad & g\left(u_{m,n}, \lambda_k, v_m\right) \\
s.t. \quad & u_{m,n} > 0 \quad \forall n \ \forall m \\
& \lambda_k > 0 \qquad \forall k \\
& v_m > 0 \qquad \forall m
\end{aligned} \tag{14}$$

where $u_{m,n}$, λ_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:

$$g\left(u_{m.n} \ \lambda_k \ v_m\right) = \max_{\{P_{m,n,k}\}} L\left(P_{m,n,k} u_{m.n} \ \lambda_k \ v_m\right) \tag{15}$$

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

In addition, through literature [8] 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

$$\begin{aligned}
g_k\left(u_{m,n} \ \lambda_k \ v_m\right) = \max_{\{P_{m,n,k}\}} [& \sum_{m=1}^{M}\sum_{n=1}^{N} \left(1+u_{m,n}\right) B_0 Log_2\left(1+d_{m,n,k}P_{m,n,k}\right) \\
& -\gamma \sum_{m=1}^{M}\sum_{n=1}^{N} P_{m,n,k} - v_m \sum_{n=1}^{N} P_{m,n,k} \\
& -\lambda_k \sum_{m=1}^{M}\sum_{n=1}^{N} P_{m,n,k} h_{m,n,k}^{S2M}]
\end{aligned} \tag{16}$$

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

$$a^*_{m,n,k} = \begin{cases} 1 & n = \arg\max_{1\le n\le N} H_{m,n,k} \\ 0 & otherwise \end{cases} \quad (19)$$

where

$$H_{m,n,k} = \left[\left(1+u_{m,n}\right)Log_2\left(y^*_{m,n,k}d_{m,n,k}\right)\right]^+ - \frac{\left(1+u_{m,n}\right)}{Ln2}\left[1-\frac{1}{y^*_{m,n,k}d_{m,n,k}}\right]^+$$

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 $I_{\max}$, convergence condition ξ_r and the initial value $\gamma^{(1)}$.

2) Set the iteration index $i=1$ and begin the iteration.

3) for $1 \le i \le I_{\max}$

4) Solve the resource allocation with $\gamma^{(i)}$;

5) Obtain $a^{(i)}, p^{(i)}, C\left(a^{(i)}, p^{(i)}\right), P\left(a^{(i)}, p^{(i)}\right)$;

6) if $C\left(a^{(i)}, p^{(i)}\right) - \gamma^{(i)}PP\left(a^{(i)}, p^{(i)}\right) < \xi_r$ then

7) Set $\left\{a^*, p^*\right\} = \left\{a^{(i)}, p^{(i)}\right\}$ and $\gamma^* = \gamma^{(i)}$;

8) break ;

9) else

10) Set $\gamma^{(i+1)} = \dfrac{C\left(a^{(i)}, p^{(i)}\right)}{P\left(a^{(i)}, p^{(i)}\right)}$ 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:

$$u^{l+1}_{m,n} = \left[u^l_{m,n} - \xi^{l+1}_u \times \nabla u^{l+1}_{m,n}\right]^+ \quad \forall\text{m},\forall\text{n} \quad (20)$$

$$\lambda^{l+1}_k = [\lambda^l_k - \xi^{l+1}_\lambda \times \nabla\lambda^{l+1}_k]^+ \quad \forall\text{k} \quad (21)$$

$$v^{l+1}_m = \left[v^l_m - \xi^{l+1}_v \times \nabla v^{l+1}_m\right]^+ \quad \forall\text{m} \quad (22)$$

where $\nabla u^{l+1}_{m,n}$, $\nabla\lambda^{l+1}_k$ and ∇v^{l+1}_m denote the gradient utilized in the $l+1$ th iteration[15]. ξ^{l+1}_u, ξ^{l+1}_λ and ξ^{l+1}_v are the positive step sizes. Among them, the expression of the Lagrange factor gradient is as follows:

$$\nabla u^{(l+1)}_{m,n} = \sum_{k=1}^{K} a^l_{m,n,k} B_0 Log_2\left(1 + d_{m,n,k}P^l_{m,n,k} - \eta_0\right) \quad \forall\text{m},\forall\text{n} \quad (23)$$

$$\nabla\lambda^{(l+1)}_k = \delta_0 - \sum_{m=1}^{M}\sum_{n=1}^{N} a^l_{m,n,k}P^l_{m,n,k}h^{S2M}_{m,n,k} \quad \forall\text{k} \quad (24)$$

$$\nabla v^{(l+1)}_m = P^S_{\max} - \sum_{n=1}^{N}\sum_{k=1}^{K} a^l_{m,n,k}P^l_{m,n,k} \quad \forall m \quad (25)$$

where $a^l_{m,n,k}$ and $P^l_{m,n,k}$ 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 smallcells 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 I: THE SIMULATION PARAMETERS

Parameter	Value
Macro cell radius	500m
Macro user number	20
Distance between MBS and MUE	Rand(0,500)
Small cell radius	50m
SUE number in each small cell	5
Distance between SBS and SUE	Rand(0,50)
Distance between SBS and MUE	Rand(60,120)
Distance between MBS and SUE	Rand(350,420)
Noise power spectral density N_0	-174dBm/Hz
MBS transmission power P^M	45dBm
System bandwidth B_0	4MHz
Resource block number K	20
Circuit power consumption P_C^S	20dBm
SUE data probability requirement η_0	60Kbps
Path loss model SBS-to-UE	$31.5+35.0*\log_{10}^{(d)}$
Path loss model MBS-to-UE	$31.5+40.0*\log_{10}^{(d)}$

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.

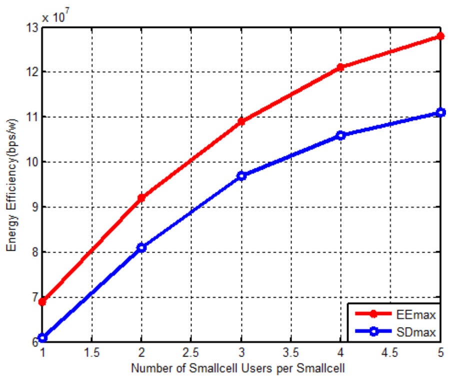

Fig. 2. The energy efficiency in different algorithm with different number of Smallcell users per Smallcell.

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.

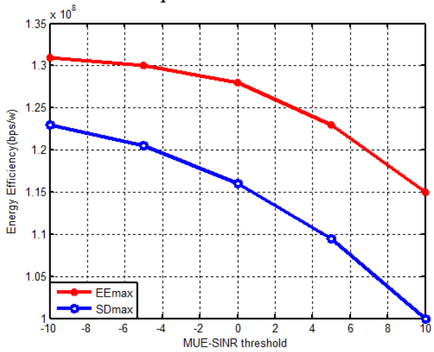

Fig. 3. The energy efficiency in different algorithm with different MUE-SINR threshold

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.

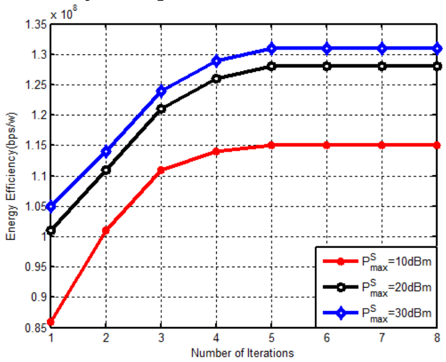

Fig. 4. Energy efficiency (bps/W) versus number of iterations with different maximum transmit power of each SBS

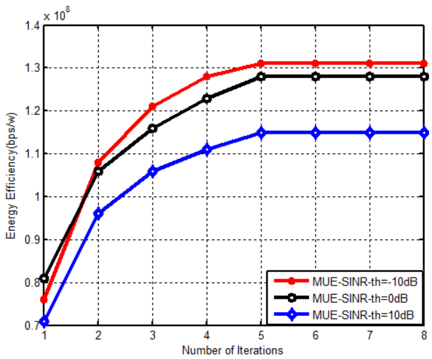

Fig. 5. Energy efficiency (bps/W) versus number of iterations with different cross-tier interference constraints

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.

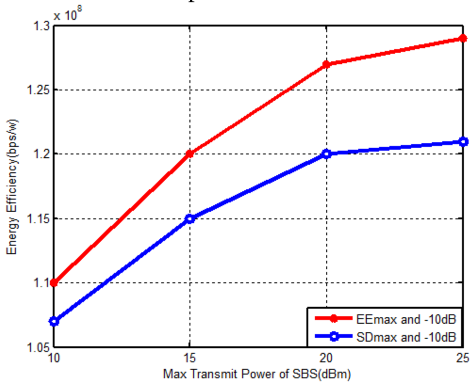

Fig. 6. Energy efficiency (bps/W) versus transmit power of SBS and cross-tier interference constraints

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 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.

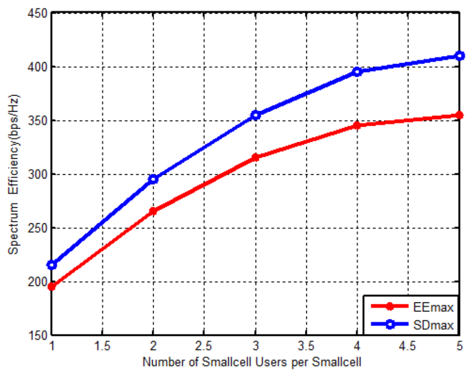

Fig. 7. The spectrum efficiency in different algorithm with different number of Smallcell users per Smallcell

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.

ACKNOWLEDGMENT

This work was supported by the National Natural Science Foundation of China under Grant No.61272506 and the Foundation of Beijing Engineering and Technology Center for Convergence Networks and Ubiquitous Services.

REFERENCES

[1] V. Chandrasekhar, J. G. Andrews, and A. Gatherer, "Femtocell networks: A Survey," *IEEE Communications Magazine*, vol. 46, no. 9, pp. 59-67, 2008.

[2] D. Lopez-Perez, I. Guvenc, G. D. L. Roche, M. Kountouris, T. Q. S. Quek, and J. Zhang, "Enhanced intercell interference coordination challenges in heterogeneous networks," *IEEE Wireless Communications*, vol. 18, no. 3, pp. 22-30, 2011.

[3] D. C. Oh, H. C. Lee, and Y. H. Lee, "Power control and beamforming for femtocells in the presence of channel uncertainty," *IEEE Trans. on Vehicular Technology*, vol. 60, no. 6, pp. 2545-2554, July 2011.

[4] X. Kang, R. Zhang, and M. Motani, "Price-Based resource allocation for spectrum-sharing femtocell networks: A stackelberg game approach," in *Proc. IEEE Global Telecommunications Conference*, 2011, pp. 1-5.

[5] C. G. Yang, J. D. Li, X. H. Jiang, and A. Anpalagan, "Interference-Aware spectral-and-energy efficiency tradeoff in heterogeneous networks," in *Proc. IEEE Wireless Communications and Networking Conference*, 2015, pp. 819-824.

[6] X. Sun and S. W. Wang. "Resource allocation scheme for energy saving in heterogeneous networks," *IEEE Trans. on Wireless Communications*, vol. 14, no. 8, pp. 4407-4416, Aug. 2015.

[7] L. Giupponi and C. Ibars, "Distributed interference control in OFDMA-Based femtocells," in *Proc. IEEE International Symposium on Personal, Indoor and Mobile Radio Communications*, 2010, pp. 1201-1206.

[8] M. Tao, Y. C. Liang, and F. Zhang, "Resource allocation for delay differentiated traffic in multiuser OFDM systems," *IEEE Trans. on Wireless Communications*, vol. 7, no. 6, pp. 2190-2201, June 2008.

[9] M. Peng, K. Zhang, J. Jiang, J. H. Wang, and W. B. Wang, "Energy-Efficient resource assignment and power allocation in heterogeneous cloud rado access networks," *IEEE Trans. on Vehicular Technology*, vol. 64, no. 11, pp. 5275-5287, Nov. 2015.

[10] X. Xiao, X. M. Tao, and J. H. Lu, "QoS-Aware energy-efficient radio resource scheduling in multi-user OFDMA systems," *IEEE Communications Letters*, vol. 17, no. 1, pp. 75-78, 2013.

[11] J. Zhang, Z. Zhang, K. Wu, and A. Huang, "Optimal distributed subchannel, rate and power allocation algorithm in OFDM-Based two-tier femtocell networks," in *Proc. IEEE 71st Vehicular Technology Conference*, 2010, pp. 1-5.

[12] X. Chen, H. L. Xia, Z. M. Zeng, S. Wu, and Y. Lu, "Energy-Efficient heterogeneous networks for green communications by inter-layer interference coordination," in *Proc. International Symposium on Wireless Personal Multimedia Communications*, 2014, pp. 70-74.

[13] W. Dinkelbach, "On nonlinear fractional programming," *Management Science*, vol. 13, no. 7, pp. 492-498, 1967.

[14] J. Kim and D. H. Cho, "A joint power and subchannel allocation scheme maximizing system capacity in indoor dense mobile communication systems," *IEEE Trans. on Vehicular Technology*, vol. 59, no. 9, pp. 4340-4353, Nov. 2010.

[15] L. Rodrigues and S. Boyd, "Piecewise-Affine state feedback using convex optimization," in *Proc. IEEE American Control Conference*, vol. 6, pp. 5164-5169, 2004.

Lingyun Feng, is a graduate student in the School of Computer & Communication Engineering, University of Science and Technology Beijing, China. She received a Bachelor degree from Tangshan College. Her research areas are wireless communications and heterogeneous network.

Yueyun Chen, is a professor in the School of Computer & Communication Engineering, University of Science and Technology Beijing, China. She received a Bachelor degree from South China University of Technology, and a Master degree and a Ph.D. from Beijing Jiaotong University. Her current research interests include wireless and mobile communications, Massive MIMO, signal processing, radio resource management, cognitive radio, millimeter wave communications, optimization theory on communications.

Xinzhe Wang, is a graduate student in the School of Computer & Communication Engineering, University of Science and Technology Beijing, China. She received a Bachelor degree from North China University of Science and Technology. Her research areas are wireless communications and coordination multipoint.