Interference Management for Energy Saving in Heterogeneous Networks

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***Abstract*—In this paper, we study how to save energy in Heterogeneous Networks (HetNets), which is introduced to the next generation cellular systems. A HetNet based cellular system consists of a mix of macrocells and low power nodes, such as picocells, femtocells and relays, making the systematic power controlling more complex than the conventional ones. The major difficulty for power control in HetNets is the mutual interference among cells with different transmission power. So interference management is very important for the next generation cellular networks. We try to minimize the total power consumption while guaranteeing users' rate requirements, to save energy and keep the user's QoS from degenerating. Our general problem formulation leads to a nonconvex optimization problem which is generally hard to solve. We derive the lower bound of user's achievable rates with given power consumption and develop an efficient iterative algorithm to deal with the intractable optimization task. Numerical results show that our proposed algorithm performs well for practical wireless scenarios.**

I. Introduction

Investigations show that mobile data traffic throughout the world grows exponentially and reaches about 3.6 exabytes per month, 39 times increase from 2009 by 2014 [**?**]. However, radio spectrum is the scarce natural resource and very crowded in the band for mobile communications, which is the bottleneck for the ever increasing mobile service applications. Though some promising spectrum utilization schemes have been proposed [**?**, **?**], most of them are far from implementation because of technical limitations. A practical solution to such a spectrum crisis is Heterogeneous Network (HetNet), which consists of infrastructure points with various wireless access nodes, such as macrocells, picocells, femtocells and relays. HetNets entail a significant paradigm shift from traditional centralized macrocell-only approach to more autonomous, uncoordinated, and intelligent ones, which can improve the utilization efficiency of spectrum. However, such a shift also introduces new challenges.

In the HetNet with a mixture of macrocells and low-power cells, the main factor that decreases system capacity is the interference between cells with different transmission power, such as the interference between a macrocell/femtocell and another macrocell/femtocell, or between a macrocell and a femtocell [**?**]. In particular, femtocells are generally installed by users in an *ad-hoc* manner, not planned by network operators, making the interference management (IM) in HetNets more difficult because the centralized power control is impossible in this instance.

To mitigate interference, traditional frequency reuse schemes can be used, such as fractional frequency reuse [**?**], which involves partitioning the available spectrum into subbands and assigning each subband to a cell to minimize interference, or adapts the fractional frequency reuse assignments based on interference levels, as well as scheduling users with a given subband based on channel quality measurement fed back from mobile users. A dynamic IM algorithm that introduces a concept of reference user is proposed in [**?**], where only one victim user in each subchannel is considered. In [**?**], interference coordination is introduced to mitigate the cochannel interference arising from range expansion. Interference cancellation is investigated in [**?**], which generally regenerates interfering signals and subsequently substracts them from the desired ones.

In this paper, we consider the IM problem in the downlink of an Orthogonal Frequency Division Multi-Access (OFDMA) cellular system. We try to save energy as much as possible while keeping the required QoSs of all users, which is different from the existing throughput-oriented targets in most of the existing works. We focus on how to minimize the total power consumption of all cells, or base stations (BSs). An efficient iterative algorithm is developed for the optimal power distribution to save energy while meeting all users' QoS requirements.

The rest of this paper is organized as follows. System model and problem formulation are stated in Section II. In Section III, we propose the resource allocation algorithm. Numerical results and discussions are given in Section IV. Conclusion is drawn in Section V.

II. System Model and Problem Formulation

A. System Model

Consider the downlink of a heterogeneous cellular system shown in Fig.1. The sets of BSs in macrocells and low-power cells are denoted as $\mathcal{N}_{macro}$ and $\mathcal{N}_{low}$, respectively. Denote $\mathcal{K} = \{1, ..., K\}$ and $\mathcal{N} = \mathcal{N}_{macro} \cup \mathcal{N}_{low} = \{1, 2, \ldots, N\}$ as the set of users and BSs, respectively. Each user can be connected to a single BS. Denote $\mathcal{K}_n$ as the (nonempty) set of users associated with BS n, i.e., $\mathcal{K} = \mathcal{K}_1 \cup \cdots \cup \mathcal{K}_n$ and $\mathcal{K}_n \cap \mathcal{K}_m = \emptyset$, for $n \neq m$. The total transmission power of BS n is limited to $P_{n,max}$. Normally, the maximum BS transmission power in a macrocell (e.g., 46 dBm) is much higher than that of a low-power cell (e.g., 30 dBm). As a result, the coverage area of a low-power cell is usually much smaller

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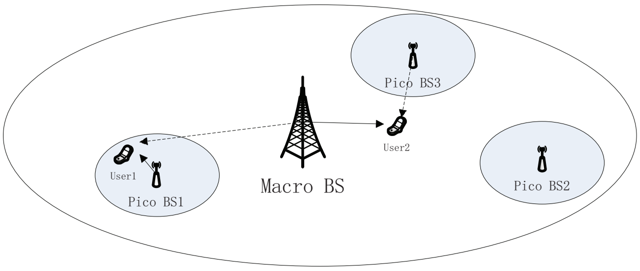

Fig. 1. An exemplary system setup, where the solid line and the dashed lines represent a communication link and cochannel interfering links for user in macrocell.

than a macrocell. If a user is within the coverage of a low-power cell, it will be served by this low-power BS; otherwise, it is served by the the macrocell BS. The total bandwidth is B (20MHz), which is available for both macrocells and low-power cells. Each user $k \in \mathcal{K}$ requires a minimal transmission rate $R_{k,min}$.

The bandwidth is divided into S OFDM subchannels which can be used by any BS for transmitting data. The set of subchannels is denoted as $\mathcal{S} = \{1, 2, \ldots, S\}$. Each BS needs to determine (i) which user is scheduled on which subchannel and (ii) how much power is allocated for the scheduled user on this subchannel. We define a binary variable $A_{n,s,k}$ for subchannel assignment,

$$A_{n,s,k} = \begin{cases} 1 & \text{subchannel } s \text{ of BS } n \text{ is allocated to user } k, \\ 0 & \text{otherwise.} \end{cases}$$

We stack $\{A_{n,s,k}\}_{k=1}^{K}$ into the vector $\mathbf{A}_{n,s} = [A_{n,s,1}, ..., A_{n,s,K}]$, and stack $\mathbf{A}_{n,s}$'s of all users in cell n to a matrix $\mathbf{A}_n$ column by column. Denote $\mathbf{A} = [\mathbf{A}_1, ..., \mathbf{A}_N]$.

Define p_s^n as the proportion of $P_{n,max}$ allocated to subchannel s by BS n. We stack $\{p_s^n\}_{n=1}^{N}$ into an $N \times 1$ vector $\mathbf{p}_s = [p_s^1, ..., p_s^N]$, and stack $\{\mathbf{p}_s\}_{s=1}^{S}$ into an $N \times S$ matrix $\mathbf{P}$.

For a given power vector $\mathbf{p}_s$, the rate of user k served by BS n can be written as

$$R_k = \sum_{s=1}^{S} A_{n,s,k} \cdot R_k(\mathbf{p}_s), \tag{1}$$

where $R_k(\mathbf{p}_s)$ stands for the rate of subchannel s of BS n used by user k , which can be also calculated as follows,

$$R_k(\mathbf{p}_s) = \frac{B}{S} \ln(1 + \frac{\gamma_{n,k,s}(\mathbf{p}_s)}{\Gamma}), \tag{2}$$

where $\gamma_{n,k,s}(\mathbf{p}_s)$ is the signal-to-interference-plus-noise ratio (SINR), and Γ represents the SINR gap [?]. Particularly, $\gamma_{n,k,s}(\mathbf{p}_s)$ can be calculated as

$$\begin{aligned} \gamma_{n,k,s}(\mathbf{p}_s) &= \frac{g_s^{k,n} p_s^n P_{n,max}}{\sum_{m \neq n} g_s^{k,m} p_s^m P_{m,max} + \sigma_s^k} \\ &= \frac{p_s^n}{I_{n,k,s}(\mathbf{p}_s)}, \end{aligned} \tag{3}$$

where

$$I_{n,k,s}(\mathbf{p}_s) = x_{n,k,s} + \sum_{m \neq n} p_s^m y_{n,k,s},$$

$$x_{n,k,s} = \frac{\sigma_s^k}{g_s^{k,n} P_{n,max}},$$

and

$$y_{n,k,s} = \frac{g_s^{k,m} P_{m,max}}{g_s^{k,n} P_{n,max}}.$$

$g_s^{k,n}$ is the channel gain between BS n and user k on subchannel s; σ_s^k is the noise power spectrum density. In this paper, we take into account the path loss, log-normal shadowing and fast fading to get the channel gain.

B. Problem Formulation

As mentioned above, $\mathbf{A}$ and $\mathbf{P}$ are the user association indicator and power allocation indicator, respectively. Our target is to find an optimal $\mathbf{A}$ and $\mathbf{P}$ to minimize the power consumption of all BSs, while keeping the rate of each user above a predefined threshold. The optimization problem can be formulated as follows,

$$\begin{aligned} \min_{\mathbf{A},\mathbf{P}} \quad & \textstyle\sum_{n \in N} \sum_{s \in S} p_s^n P_{n,max} \\ s.t. \quad & C_1 : \textstyle\sum_{s=1}^{S} p_s^n \leq 1, \forall n \in \mathcal{N}, \\ & C_2 : \sum_{k \in \mathcal{K}_n} A_{n,k,s} \leq 1, \forall n \in \mathcal{N}, s \in \mathcal{S}, \\ & C_3 : A_{n,k,s} \in \{0, 1\}, \forall k \in \mathcal{K}_n, \\ & C_4 : R_k \geq R_{k,min}, \forall k. \end{aligned} \tag{4}$$

III. Our Algorithm

Eq.(4) is hard to solve because it involves both binary integer variable $A_{n,k,s}$'s and real variable p_s^n's. In this paper, we solve the (4) with a two-step procedure: subchannel assignment; power optimization.

A. Subchannel Assignment

By initializing the power vector as $[\mathbf{P}^0]_{n,s} = (1/S), \forall n, \forall s$, we propose an efficient subchannel allocation scheme to figure out the binary variables $A_{n,k,s}$, specifying a subchannel allocation assignment for each BS n.

Let Ω_k denotes the subchannels set employed by the kth user. The framework of the subchannel allocation scheme is described in Table I, which consists of two steps. First, we allocate each user subchannels to meet the minimal rate requirement. Then the remaining subchannels are allocated to the users with the highest SINR. The intuitiveness of the Step 1 is that the user whose rate is the farthest away from its target one has a priority to get a subchannel among the available ones. This procedure continues until all users' rate requirements are satisfied. Again, the subchannel with the highest achievable rate associated with a user will be chosen.

B. A Concave Lower Bound of User Rate

However, even for a given subchannels assignment $\mathbf{A}$, there is still no efficient algorithm to solve the (4), because the (3) is nonconvex, as a result of the interference item. Here, we establish a concave lower bound of user rate to replace the

TABLE I
ALGORITHM 1

Initialization:
$\mathcal{S}_t$=$\mathcal{S}$, Ω_k=$\emptyset$, $\forall k$;
Set the users' rate to zero: $R_k = 0$, for $k = 1, 2, ..., K$;
Step 1
While $\mathcal{S}_t \neq \emptyset$ and $R_k < R_{k,min}$, $1 \leq k \leq K$
  Find k^* satisfies $R_{k^*} - R_{k,min} \leq R_k - R_{k,min}$ for all $k \in K$;
  Find s^* satisfies $\gamma_{n,k^*,s^*} \geq \gamma_{n,k^*,s}$, $\forall s \in \mathcal{S}_t$;
  Update $R_{k^*} = R_{k^*} + \log(1 + \gamma_{n,k^*,s^*})$;
  Update $\Omega_{k^*} = \Omega_{k^*} \cup s^*$,$\mathcal{S}_t = \mathcal{S}_t \setminus s^*$;
Endwhile
Step 2
For $i = 1$ to length($\mathcal{S}_t$);
  For $s^* = \mathcal{S}_{t_i}$, find s^* satisfies $\gamma_{n,k^*,s^*} \geq \gamma_{n,k^*,s}$;
  Update $\Omega_{k^*} = \Omega_{k^*} \cup s^*$;
Endfor

original one, which is associated with a given power allocation $\mathbf{P}^*$ [**?**]. Define

$$R^*_{n,k,s}(e^{\mathbf{q}}) = \alpha^*_{n,k,s} \cdot \ln\left(\gamma_{n,k,s}(e^{\mathbf{q}})\right) + \beta^*_{n,k,s}, \tag{5}$$

$$\alpha^*_{n,k,s} = \frac{\gamma_{n,k,s}(\mathbf{p}^*_s)}{\Gamma + \gamma_{n,k,s}(\mathbf{p}^*_s)}, \tag{6}$$

$$\beta^*_{n,k,s} = R_{n,k,s}(\mathbf{p}^*_s) - \alpha^*_{n,k,s} \cdot \ln\left(\gamma_{n,k,s}(\mathbf{p}^*_s)\right), \tag{7}$$

where $\mathbf{q}$ is an $N \times 1$ vector, and $\mathbf{p}^*_s$ denotes the sth column of $\mathbf{P}^*$. Note that $\mathbf{P}^*$ belongs to the set $P_+ = \{P | \forall n, \forall s, p_{n,s} \in (0, 1]\}$, to guarantee that $\forall k, \forall n, \forall s, \gamma_{n,k,s}(\mathbf{P}^*_s) > 0$, $\forall k, \forall n, \forall s, \alpha^*_{n,k,s} > 0$. We have the following theorem:

Theorem 1. *$R_{n,k,s}(e^{\boldsymbol{q}}) \geq R^*_{n,k,s}(e^{\boldsymbol{q}})$ and the equality holds when $e^{\boldsymbol{q}} = \boldsymbol{p}^*_s$; $R^*_{n,k,s}(e^{\boldsymbol{q}})$ is a concave function of $\boldsymbol{q}$.*

Proof: To prove Theorem 1, we first show the inequality

$$\ln(1 + z) \geq \ln(1 + z^*) + \frac{z^*}{1 + z^*}(\ln(z) - \ln(z^*)), \tag{8}$$

where the equality holds when $z = z^*$ [**?**]. Particularizing z and z^* with $(\gamma_{n,k,s}(e^{\mathbf{q}}))/\Gamma$ and $\gamma_{n,k,s}(\mathbf{p}^*_s)/\Gamma$, respectively, $R_{n,k,s}(e^{\mathbf{q}}) \geq R^*_{n,k,s}(e^{\mathbf{q}})$ follows and the equality holds when $e^{\mathbf{q}} = \mathbf{p}^*_s$.

Then we expand $R^*_{n,k,s}(e^{\mathbf{q}})$ as

$$R^*_{n,k,s}(e^{\mathbf{q}}) = \alpha^*_{n,k,s} \cdot (q_n - \ln\left(I_{n,k,s}(e^{\mathbf{q}})\right)) + \beta^*_{n,k,s} \tag{9}$$

where q_n is the nth entry of $\mathbf{q}$. $\ln\left(I_{n,k,s}(e^{\mathbf{q}})\right) = \ln\left(x_{n,k,s} + \sum_{m \neq n} y_{n,k,s} e^{q_m}\right)$ is a convex function of $\{q_m\}_{m \neq n}$, refer to [**?**] and appendix therein for details. Since $\alpha^*_{n,k,s} > 0$, it can be easily shown that $R^*_{n,k,s}(e^{\mathbf{q}})$ is a concave function of $\mathbf{q}$. ■

Define

$$R^*_k(A_{n,k,s}, e^{\mathbf{Q}}) = \sum_{n=1}^{N}\sum_{s=1}^{S} A_{n,k,s} \cdot R^*_{n,k,s}(e^{\mathbf{q}}), \tag{10}$$

where $\mathbf{Q}$ is an $N \times S$ matrix whose the sth column is $\mathbf{q}_s$. Based on Theorem 1, we know that $R^*_k(A_{n,k,s}, e^{\mathbf{Q}})$ is a concave function of $\mathbf{Q}$, as well as a lower bound of R_k. Besides, the bound is tight when $e^{\mathbf{Q}} = \mathbf{P}^*$. In this way, we transform the original nonconvex problem into a convex one.

TABLE II
ALGORITHM 2

Initialize:$i = 0$, $\mathbf{P}^0 = \mathbf{P}$;
  repeat
    Solve (11) with $\mathbf{P}^* = \mathbf{P}^i$ for $\mathbf{Q}_0$ using Algorithm 3;
    $\mathbf{P}^{i+1} = e^{\mathbf{Q}_0}$;
    $i = i + 1$;
  until $||vec(\mathbf{Q}_0 - \mathbf{Q}^*)|| < \Omega_1$ or $i = I$
Output: $\mathbf{P} = \mathbf{P}^I$.

C. Power Allocation Optimization

Define the sets $\boldsymbol{P}_\epsilon = \{\mathbf{P} | \forall n, \forall s, P_{n,s} \in [e^\epsilon, 1]\}$ and $\boldsymbol{Q}_\epsilon = \{\forall n, \forall s, q_{n,s} \in [\epsilon, 0]\}$, ϵ is a prescribed negative value, replace R_k with $R^*_k(A_{n,k,s}, e^{\mathbf{Q}})$ in the (4), we can get a parameterized convex approximation to the (4) as follows,

$$\begin{aligned} \min_{\mathbf{Q}} \quad & \sum_{n=1}^{N}\sum_{s=1}^{S} e^{q_{n,s}} \cdot P_{n,max} \\ s.t. \quad & C_1 : \mathbf{Q} \in \boldsymbol{Q}_\epsilon, \\ & C_2 : \textstyle\sum_{s=1}^{S} e^{q_{n,s}} \leq 1, \\ & C_3 : R^*_k(A_{n,k,s}, e^{\mathbf{Q}}) \geq R_{k,min}, \forall k. \end{aligned} \tag{11}$$

Once get a feasible power allocation for the (4), we can assign it to $\mathbf{P}^*$ and solve the (11) for $\mathbf{Q}_0 \in \boldsymbol{Q}_\epsilon$. Then $\mathbf{P}_0 = e^{\mathbf{Q}_0}$ is guaranteed to be feasible for the (4), which is at least as good as $\mathbf{P}^*$.

We develop an iterative power allocation algorithm for a given $\mathbf{A}$, which is depicted in Table II, where i denotes the iteration number ($i > 0$), and $\mathbf{P}^i$ denotes the tentative power allocation at the ith iteration. In each iteration, we solve the (11) with $\mathbf{P}^* = \mathbf{P}^i$ to get the optimal solution $\mathbf{Q}_0$, and set $\mathbf{P}^{i+1} = e^{\mathbf{Q}_0}$.

For a given $\mathbf{A}$, denote the dual variables related to the power constraint of BS n and the rate constraint of user k by λ_n and ν_k, respectively. We then stack all λ_n and ν_k into a vector $\omega = [\lambda_1, ..., \lambda_N, \nu_1, ..., \nu_K]$.

Reformulate the dual function of the (11) as

$$\begin{aligned} \min_{\mathbf{Q}} \quad & \sum_{n=1}^{N}\sum_{s=1}^{S} e^{q_{n,s}} P_{n,max} + \sum_{n=1}^{N} \lambda_n (\sum_{s=1}^{S} e^{q_{n,s}} - 1) \\ & + \sum_{k=1}^{K} \nu_k (R_{k,min} - R^*_k(A_{n,k,s}, e^{\mathbf{Q}})) = D(\omega), \end{aligned} \tag{12}$$

and the dual problem is

$$\begin{aligned} \max_{\omega} \min_{\mathbf{Q}} \quad & \sum_{n=1}^{N}\sum_{s=1}^{S} e^{q_{n,s}} P_{n,max} + \sum_{n=1}^{N} \lambda_n (\sum_{s=1}^{S} e^{q_{n,s}} - 1) \\ & + \sum_{k=1}^{K} \nu_k (R_{k,min} - R^*_k(A_{n,k,s}, e^{\mathbf{Q}})) = \max_{\omega} D(\omega). \end{aligned} \tag{13}$$

TABLE III
ALGORITHM 3

1:	**Initialize:** $i = 0$, ω^0;
2:	**repeat**
3:	Compute Q_{ω^i} with the method proposed in Section IV-D;
4:	Compute ω^{i+1};
5:	$i = i + 1$;
6:	**until** $\|\omega^i - \omega^{i-1}\| < \Omega_2$
7:	**Output:** Q_{ω^i} is the optimal solution to (11).

Define $Q_\omega = \arg D(\omega)$. To solve the (11), we can first find out the optimal dual variable $\omega^* = \arg\max_{\omega} D(\omega)$, and then compute Q_{ω^*} as the optimal solution to the (11). Then we can work out ω^* and Q_{ω^*} by using the method proposed in [?]. We adopt Algorithm 3 shown in Table III to solve the problem, where i denotes the iteration number ($i \geq 0$), ω^i represents the dual variable produced at the ith iteration, and Ω_2 is a prescribed small positive.

First, we initialize the dual variable ω^0. In each iteration, $\mathbf{Q}_{\omega^i}$ is computed with the algorithm proposed in Section IV-D. When $\mathbf{Q}_{\omega^i}$ is worked out, we can update the dual variable ω^i by solving the (13). The (13) can be solved by the ellipsoid method or subgradient method [?]. We compute the dual variables as follows,

$$\lambda_n^{i+1} = [\lambda_n^i + s^i(\sum_{s=1}^{S} e^{q_{n,s}} - 1)]^+, \tag{14}$$

$$\nu_k^{i+1} = [\nu_k^i + s^i(R_{k,min} - R_k^*(A_{n,k,s}, e^{\mathbf{Q}}))]^+, \tag{15}$$

where the superscript i indicates the associated dual variables is an entry in ω^i, $[x]^+ = \max\{0, x\}$, and s^i is step size which is a sufficiently small positive. The convergence of Algorithm 3 is guaranteed if s^i is sufficiently small. The algorithm is terminated when $\|\omega^i - \omega^{i-1}\|$ is smaller than a prescribed positive Ω_2, then $\mathbf{Q}_{\omega^i}$ yielded in the last iteration is taken as the optimal solution to the (11).

D. On the Computing of $\mathbf{Q}_{\omega^i}$

To find $\mathbf{Q}_{\omega^i}$, we need to solve a constrained optimization problem over set $\boldsymbol{Q}_\epsilon$, namely $Q_{\omega^i} = \arg D(\omega^i)$. Because of the convexity of $D(\omega^i)$, we can adopt a gradient-projection based iterative algorithm, which features simplicity as well as guaranteed convergence to find $\mathbf{Q}_{\omega^i}$. Specifically, this method begins with initializing $\mathbf{Q}$ by $\mathbf{Q}^*$ if $i = 0$, otherwise, by $\mathbf{Q}^{i-1}$. Then, $\mathbf{Q}$ is iteratively updated by $\mathbf{Q} = [\mathbf{Q} - \tau \cdot B]_{\boldsymbol{Q}_\epsilon}$, where $\mathbf{B}$ is a matrix containing the gradients of $D(\omega^i)$ with respect to every entry of $\mathbf{Q}$, $[\cdot]_{\boldsymbol{Q}_\epsilon}$ is the operator of projection into $\boldsymbol{Q}_\epsilon$, and τ is a prescribed small positive value that guarantees convergence of the gradient-projection based algorithm. By simple mathematical arrangement, every entry of $\mathbf{Q}$ can be updated by

$$\forall n, \forall s, q_{n,s} = \begin{cases} \epsilon & \text{if } q_{n,s} - \tau \cdot [\mathbf{B}]_{n,s} \leq \epsilon \\ 0 & \text{if } q_{n,s} - \tau \cdot [\mathbf{B}]_{n,s} \geq 0 \\ q_{n,s} - \tau \cdot [\mathbf{B}]_{n,s} & \text{otherwise} \end{cases}$$

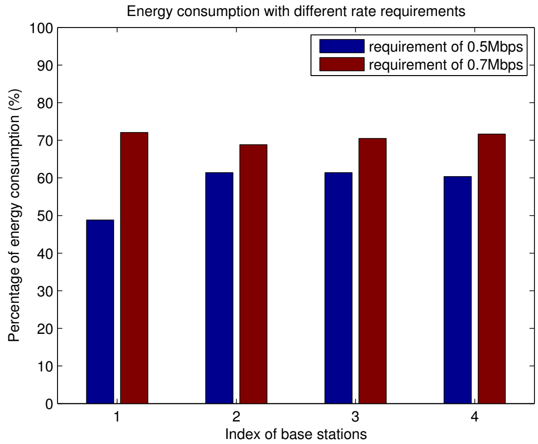

Fig. 2. Energy consumption of each cell with users' rate requirements of 0.5Mbps and 0.7Mbps.

where $[\mathbf{B}]_{n,s}$ is derived as

$$[\mathbf{B}]_{n,s} = e^{q_{n,s}} P_{n,max} + \lambda_n(e^{q_{n,s}}) - \sum_{k=1}^{K} \nu_k (A_{n,k,s}\alpha_{n,k,s}^* - \sum_{m=1,m\neq n}^{N} A_{m,k,s}\alpha_{m,k,s}^* \frac{e^{q_{n,s}} P_{n,max} g_s^{k,n}}{\sum_{j=1,j\neq m}^{N} e^{q_{j,s}} P_{j,max} g_s^{k,j} + \sigma_s^k}). \tag{16}$$

The iteration is terminated when $\|vec([\mathbf{Q} - \tau \cdot B]_{\boldsymbol{Q}_\epsilon}) - \mathbf{Q}\|$ is smaller than a prescribed value Δ. Then $\mathbf{Q}$ produced by the last iteration is taken as $\mathbf{Q}_{\omega^i}$.

IV. NUMERICAL EXPERIMENTS

Consider the downlink of a cellular system, where 3 picocells are located with uniform intervals around a circle of radius $R_p = 400m$, and a macrocell BS is located at the center of the circle. Users are uniformly distributed within the coverage of each cell. Path loss is $131.1 + 42.8log10(R[km])$ for NLOS (Non Line of Sight) and $103.4 + 24.2log10(R[km])$ for LOS (Line of Sight) with the probability function of $Prob(R) = \min(0.018/R, 1) * (1 - \exp(-R/0.063)) + \exp(-R/0.063)$ for macro BS with 10dB penetration loss; $145.4 + 37.5log10(R[km])$ for NLOS and $103.8 + 20.9log10(R[km])$ for LOS with the probability function of $Prob(R) = 0.5 - \min(0.5, 5\exp(-0.156/R)) + \min(0.5, 5\exp(-R/0.03))$ for pico BS with 10dB penetration loss due to walls are adopted [?]. The maximum power budgets of macrocell and picocell BSs are 40 W and 1 W, respectively. $\Gamma = 0$ dB, $\epsilon = -10$, $e^\epsilon = 4.54 \times 10^{-5}$, $\tau = 10^{-2}$, $\Omega_1 = \Omega_2 = \Delta = 10^{-1}$. All results are obtained by averaging 1000 experiments.

Fig.2 shows the energy consumption as a function of users' rate requirements. BS 1 is the macrocell and the others are the picocells. We take the cellular system without interference management as reference (100% energy consumption). As can be seen from Fig.2, our proposed algorithm can save much

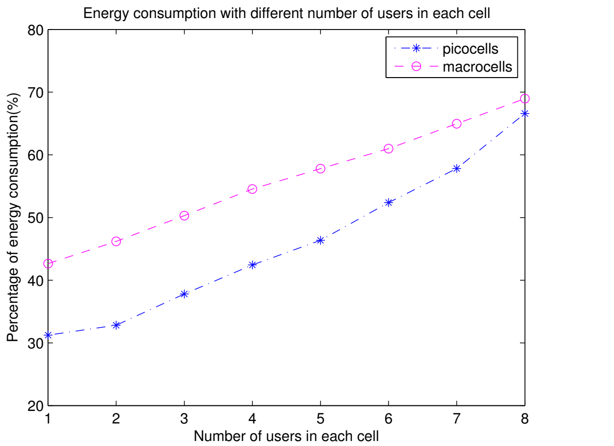

Fig. 3. Energy consumption of macrocell and picocell with different number of users.

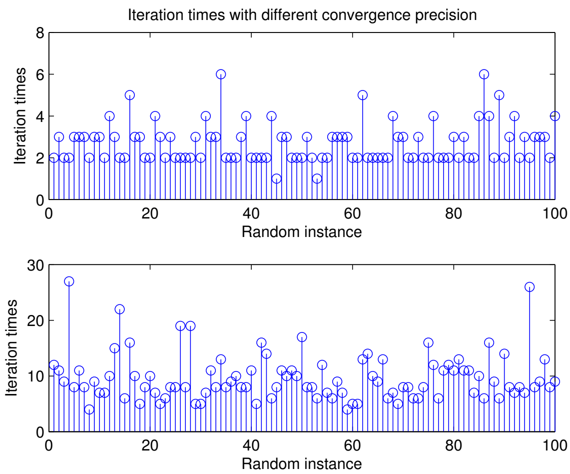

Fig. 4. Number of iterations with different convergence precision (Ω_1).

energy (about 40% for the $0.5M$ case). We can also see that more energy is consumed as the increase of users' rate requirements.

Fig.3 shows the energy comsumption as a function of the number of users. When the number of users is small, the energy consumption of picocells is much less than the macrocell. However, as the number of users increases, the energy consumption of picocells increases rapidly. The reason is that the high transmission power of the macrocell results in much interference to the link between the picocells and the users served by them. The picocells need more power to maintain the required SINRs.

Finally, we investigate the convergence of the proposed algorithm. As can be seen in Fig.4, the number of iterations is stable when Ω_1 is low and varies in a narrow range when Ω_1 decreases. Fig.2-4 show that the proposed algorithm can effectively manage the interference to reduce the total energy consumption of all BSs.

V. Conclusion

In this paper, we studied the interference management problem in heterogeneous networks for energy saving while guaranteeing the demand of users' rate. We give a lower bound of user's rate , based on which we develop algorithms for sub-channels assignment and power distribution. The effectiveness and the efficiency of our proposed algorithms are validated by numerical results.

Acknowledgement

This work was partially supported by the Jiang-suSF (BK2011051), Huawei Technologies Co., Ltd (Y-B2012120195,YBWL2012SKL09) and the Fundamental Research Funds for the Central Universities.

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