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Energy efficiency based joint cell selection and power allocation scheme for HetNets☆

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ABSTRACT

Heterogeneous networks (HetNets) composed of overlapped cells with different sizes are expected to improve the transmission performance of data service significantly. User equipments (UEs) in the overlapped area of multiple cells might be able to access various base stations (BSs) of the cells, resulting in various transmission performances due to cell heterogeneity. Hence, designing optimal cell selection scheme is of particular importance for it may affect user quality of service (QoS) and network performance significantly. In this paper, we jointly consider cell selection and transmit power allocation problem in a HetNet consisting of multiple cells. For a single UE case, we formulate the energy efficiency of the UE, and propose an energy efficient optimization scheme which selects the optimal cell corresponding to the maximum energy efficiency of the UE. The problem is then extended to multiple UEs case. To achieve joint performance optimization of all the UEs, we formulate an optimization problem with the objective of maximizing the sum energy efficiency of UEs subject to QoS and power constraints. The formulated nonlinear fractional optimization problem is equivalently transformed into two subproblems, i.e., power allocation subproblem of each UE-cell pair, and cell selection subproblem of UEs. The two subproblems are solved respectively through applying Lagrange dual method and Kuhn–Munkres (K-M) algorithm. Numerical results demonstrate the efficiency of the proposed algorithm.

1. Introduction

In recent years, high-speed mobile Internet applications, such as voice over Internet protocol (VoIP), video streaming, Internet surfing, online games, etc, have experienced rapid development, which pose great challenges on the transmission performance of traditional cellular networks. Cellular heterogeneous networks (HetNets) consisting of both macro cells and small cells, such as femto cells, pico cells and relay nodes, etc. are expected to improve the transmission performance of data service significantly [1–3].

As small cells can be deployed densely in HetNets, it is highly possible that user equipments (UEs) might be located in the overlapped area of multiple cells, in which case UEs may be able to access various base stations (BSs) of the cells, resulting in various transmission performances due to cell heterogeneity especially in terms of channel characteristics and available network resource. Hence, the design of optimal cell selection scheme is of particular importance for it may affect user quality of service (QoS) and network performance significantly.

Cell selection or network selection problem has been considered in the literature. In [4], the authors propose a load-aware cell selection approach for HetNets. In particular, they investigate the properties of a hierarchical (Stackelberg) Bayesian game framework, in which the macro cell dynamically chooses the offset about the state of the channel in order to guide users to perform intelligent network selection decisions between macro cell and small cell networks. The authors in [5] study the machine learning based strategies for dynamic channel selection in cognitive access points (CogAPs) of WLANs. They employ multi-layer feed forward neural network models that utilize historical traffic information from network environment to predict traffic loads of the channels. Based on the obtained load information, the CogAPs choose the best channel for serving wireless clients.

In the case that cell selection strategies have been designed for HetNets, the resource allocation schemes play an important role in affecting the transmission performance of users. References [6,7] stress the power allocation problem of HetNets. The authors in [6] study the downlink power allocation problem of HetNets consisting of femto BSs (FBSs) and MBSs, and formulate the power allocation problem of the FBSs as a non-cooperative game model under the constraint of the outage probability of macro UEs (MUEs). Through solving the Nash

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equilibrium solutions of the game model, the transmit power strategies can be obtained. In [7], the authors jointly consider time domain and power domain optimization of a two-tier macro-pico HetNet. Time domain performance optimization is achieved by applying an adaptive almost blank subframes (ABS) configuration scheme which dynamically matches network resources to the real-time load of the network. To further enhance network performance and achieve the performance tradeoff between the two tiers, a utility function maximization based power control and scheduling scheme is proposed.

The authors in [8] propose a resource allocation scheme for co-channel interference avoidance in long term evolution (LTE) heterogeneous networks with universal spectrum reuse where both macro users and cognitive FBSs within the same macrocell coverage can dynamically reuse whole spectrum. The proposed scheme addresses co-channel interference by employing fractional frequency reuse for resource block (RB) allocation in the outer region of the macrocell and increasing the distance of users that reuse the same RB within the macrocell. In [9], the authors consider the interference problem in two-tier femtocell networks and propose two frequency partitioning methods to mitigate the interference between the macrocell and femtocells. The authors in [10] consider the resource allocation problem of cloud mobile gaming (CMG) on mobile devices and address the problem of making the CMG approach scalable and economically feasible by proposing a novel wireless cloud scheduler.

In [11,12], resource allocation problems and cell selection (or user association) problems are jointly considered for HetNets. In [11], the authors propose a unified static framework to study the interplay of user association and resource allocation in HetNets and formulate the joint optimization problems as non-convex integer programs. To increase the energy efficiency of the BSs in HetNets, BS on-off switching schemes are considered in [12], where the authors propose an optimal BS on-off switching and user association scheme with the objective to maximize the system energy efficiency. In [13], the authors formulate the joint BS assignment and downlink beamforming scheme in HetNets as a weighted sum rate maximization problem. Through solving the optimization problem, the optimal joint BS assignment and downlink beamforming strategies can be obtained.

References [14,15] focus on transmitting power optimization based cell selection, i.e., selecting the optimal cells for users so that the total transmitting power can be minimized under a predefined signal and interference to noise ratio (SINR) constraint. The authors in [16] propose a distributed base station association and power control scheme for HetNets which aims of maximizing the sum rate across the network. In [17], the authors consider the optimization of user and BS association in a wireless downlink cellular HetNet under the proportional fairness criterion and propose a utility maximization based joint user association and power allocation scheme.

Previous research works on joint cell association and power allocation in HetNets [14–17] mainly focus on maximizing the transmission rate or system utility, fail to consider the tradeoff between the transmission rate and energy consumption of UEs. In general, to achieve high transmission rate, large transmitting power of the UEs is required, resulting in higher energy consumption, which is highly undesired especially for energy-sensitive devices.

In this paper, we study joint cell association and power allocation problem in HetNets. To achieve the tradeoff between the transmission rate and energy consumption, we propose an energy efficient joint cell selection and power allocation scheme for UEs. To reduce the computation complexity of the scheme, candidate cells are selected among all the cells of the HetNet and the proposed scheme is then only applied to the candidate cells. We first consider a single UE case and propose an energy efficient optimization scheme which selects the optimal cell corresponding to the maximum energy efficiency of the UE. The problem is then extended to multiple UEs case. To achieve joint performance optimization of all the UEs, we formulate an optimization problem with the objective of maximizing the sum energy efficiency of UEs subject to QoS and power constraints. The formulated nonlinear fractional optimization problem is equivalently transformed into two subproblems, i.e., power allocation subproblem of each UE-cell pair, and cell selection subproblem of UEs. The two subproblems are solved respectively through applying Lagrange dual method and Kuhn–Munkres (K-M) algorithm.

The rest of the paper is organized as follows. In Section 2, the system model considered in this paper is outlined. Section 3 proposes candidate cell selection scheme. A joint cell selection and power allocation scheme is proposed for a single UE case in Section 4. In Section 5, we propose a joint cell selection and power allocation scheme for multiple UEs case. In Section 6, the optimization problem formulated is solved. Simulation results are presented in Section 7. Finally, we conclude this paper in Section 8.

2. System model

In this paper, we consider a HetNet comprising of multiple cells including macro cells, pico cells, and femto cells, etc., the coverage region of which may overlap with each other. A number of UEs located in the area of the HetNet may access the BS of various cells for information interaction. We assume that orthogonal spectrum sharing scheme is applied for the cells, i.e., various spectrum is allocated to different cells, hence no inter-cell interference exists. In addition, to avoid intra-cell interference, different time–frequency resource blocks are allocated to UEs of each cell. Fig. 1 shows the system model considered in this paper.

We denote the number of UEs as M and the number of cells as N. In this paper, we consider that UEs may select one cell for network accessing and study the problem of joint cell selection and transmitting power allocation of the UEs. For convenience, it is assumed that at certain time–frequency resource blocks, one BS can only access one UE for data forwarding and vice versa.

3. Candidate cell selection scheme

As UEs in a HetNet may have various QoS requirements, in this paper, to stress user QoS requirement on transmission rate, we assume each UE might have different data rate requirement, which poses constraints on target access cell in turn. More specifically, as some cells may not be able to meet the data rate constraint of certain UEs, they cannot be selected as the serving cell of these UEs. In this paper, to reduce the computation complexity of the proposed cell selection and power allocation scheme, we first propose a candidate cell selection scheme which selects the qualified cells based on the QoS requirements of UEs, then a joint cell selection and power allocation scheme is presented which only applies to the candidate cells of the UEs.

To offer data transmission service to a UE with a transmission rate requirement, which is in general characterized by a minimum data rate constraint, the target cell has to meet the data rate requirement. Denoting R_{ij} as the achievable data rate of the ith UE when accessing

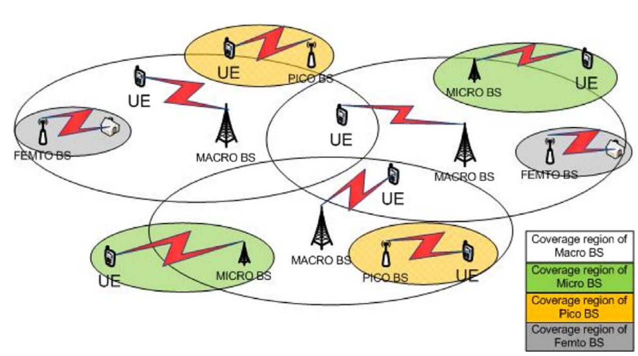

Fig. 1. System model.

the jth cell, according to Shannon formula [18], we can obtain

$$R_{ij} = B_j \log_2\left(1 + \frac{P_{ij} h_{ij}}{\sigma^2}\right) \tag{1}$$

where B_j denotes the bandwidth of the jth cell, P_{ij} denotes the transmit power of the ith UE when accessing the jth cell, h_{ij} and σ_2 denote respectively the channel gain and the noise power of the link from the ith UE to the jth cell. Without loss of generality, the noise power is assumed to be a constant for all the links of the HetNet in this paper. Denoting $R_i^{\min}$ as the minimum data rate requirement of the ith UE, the data rate constraint can be expressed as:

$$R_{ij} \ge R_i^{\min}. \tag{2}$$

P_{ij} in (1) is one of the optimization variables in our proposed cell selection and resource allocation scheme, the exact R_{ij} cannot be obtained before completing the optimization process and obtaining the optimal P_{ij}. However, as each UE may have to meet a maximum transmit power requirement due to hardware and signal processing constraint, we can instead examine the maximum achievable data rate of the ith UE when accessing the jth cell through replacing P_{ij} by its maximum value. Denoting $P_i^{\max}$ as the maximum allowable transmit power of the ith UE, the transmit power of the UE should be less than $P_i^{\max}$ and can be expressed as

$$P_{ij} \le P_i^{\max}, \quad 1 \le i \le M,\ 1 \le j \le N. \tag{3}$$

Combining (1)–(3), we obtain

$$R_{ij}^{\max} = B_j \log_2\left(1 + \frac{P_i^{\max} h_{ij}}{\sigma^2}\right) \ge R_i^{\min}. \tag{4}$$

It can be seen clearly from (4) that for given $P_i^{\max}$ and $R_i^{\min}$ of the ith UE, the jth cell has to meet certain constraints on available bandwidth resource and channel characteristics, which are characterized by B_j and h_{ij}. In other words, we can obtain that the jth cell can be selected as the target access cell of the ith UE, only if it meets the conditions specified in (4). Denote Φ as the cell set of the network and Φ_i as the set of the candidate cells of the ith UE, we obtain

$$\Phi_i = \{C_j | R_{i,j}^{\max} \ge R_i^{\min},\ C_j \in \Phi\} \tag{5}$$

where C_j denotes the jth cell.

In respect of all the candidate cells of the ith UE, i.e., $C_j \in \Phi_i$, the cell offering the optimal performance will be selected and the corresponding optimal transmitting power of the UE will be designed, as discussed in two sections below.

4. Proposed joint optimization scheme: single UE case

In this section, we consider the case that only one UE needs to select an optimal cell for accessing and design a joint cell selection and power allocation scheme for the UE. While requesting access service, the UE may tend to choose the candidate cell corresponding to the optimal transmission performance. In this paper, to stress the importance of both the transmission rate and power consumption of the UE, and to achieve the tradeoff of the two metrics, the energy efficiency of the UE on the target cell is examined and optimized in terms of the transmit power of the UE. For convenience, we refer the single UE as the first UE, i.e., we set i=1 in the formulas derived in previous sections. The energy efficiency of the UE when accessing the jth cell, denoted by η_j, can be defined as the ratio of the achievable data rate and the power consumption of the UE on the jth cell, i.e.,

$$\eta_j = \frac{R_{1,j}}{P_{1,j} + P^c} \tag{6}$$

where P^c denotes the circuit consumption power of the UE, which is assumed to be a constant for all the UEs in this paper.

To achieve high energy efficiency, the UE may prefer choosing the jth cell which offers the maximum energy efficiency among all the candidate cells as its target cell. However, it can be seen from (6) that the energy efficiency, i.e., η_j, varies with the transmit power $P_{1,j}$ for given channel and device characteristics, thus it is difficult to examine and compare the energy efficiency of the UE when accessing various cells. To stress this problem, we propose a two-step algorithm which consists of both power allocation and cell selection sub-algorithms. More specifically, for $C_j \in \Phi_i$, we first conduct optimal power allocation sub-algorithm, i.e., optimizing η_j in terms of $P_{1,j}$ to obtain the maximum η_j, denoted by η_j^*, and then apply optimal cell selection sub-algorithm, i.e., choosing the optimal cell corresponding to the maximum η_i^*.

The detail algorithm is discussed below. For the jth cell, $C_j \in \Phi_i$, the optimal power allocation problem can be formulated as:

$$\max_{P_{1,j}} \eta_j \text{s. t. } \text{C1: } R_{1,j} \ge R_1^{\min} \text{C2: } P_{1,j} \le P_1^{\max}. \tag{7}$$

For a given range of $P_{1,j}$, i.e., $0 < P_{1,j} \le P_1^{\max}$, the optimal energy efficiency of the UE when accessing the jth cell, denoted by η_j^*, can be obtained through solving above problem via numerical method or optimization techniques discussed in Section 5. Given η_j^*, $C_j \in \Phi_i$, we can then conduct optimal cell selection subalgorithm through which the j^*th cell offering the maximum η_j^* is selected as the optimal cell, i.e.,

$$C_{j^*} = \arg\max_{C_j \in \Phi_i} (\eta_j^*). \tag{8}$$

5. Proposed joint optimization scheme: multiple UEs case

In the previous section where the problem of optimal cell selection and power allocation can be solved by selecting the optimal cell that offers the maximal energy efficiency. It must be noted that, in the case that multiple UEs may access the cell simultaneously, giving the chance to each UE to select its optimal BS in the cell might not be achievable as resource competition among UEs is present. In this section, we extend the discussion to multiple UEs. Jointly considering the performance of all UEs, we propose an optimal cell selection and power allocation scheme that achieves the performances optimization of all UEs.

5.1. Joint energy efficiency formulation

The joint energy efficiency of the UEs, denoted by η, can be expressed as the sum of the energy efficiency of all the UEs and is given by

$$\eta = \sum_{i=1}^{M} \sum_{j=1}^{N} \beta_{ij} \eta_{ij} \tag{9}$$

where η_{ij} denotes the corresponding energy efficiency when the ith UE accesses the jth cell, and can be expressed as

$$\eta_{ij} = \frac{R_{ij}}{P_{ij} + P^c} \tag{10}$$

and $\beta_{ij} \in \{0, 1\}$ denotes the selection variable between the ith UE and the jth cell. That is, if the ith UE accesses the jth cell, $\beta_{ij} = 1$, otherwise, $\beta_{ij} = 0$.

5.2. Optimization constraints

5.2.1. Selection variable constraint

In this paper, we assume that each cell can at most access one UE and vice versa, hence, the constraints can be expressed as:

$$\sum_{j=1}^{N} \beta_{ij} \le 1, \quad 1 \le i \le M \tag{11}$$

$$\sum_{i=1}^{M}\beta_{ij}\le 1,\quad 1\le j\le N \tag{12}$$

5.2.2. Data rate constraint

Let R_i denote the data rate of the ith UE, it can be calculated as

$$R_i=\sum_{j=1}^{N}\beta_{ij}R_{ij}. \tag{13}$$

The data rate constraint of the ith UE can be expressed as

$$R_i\le R_i^{\min},\quad 1\le j\le N. \tag{14}$$

In addition, the maximum transmit power constraint must be met by UEs, which is expressed in (3).

5.3. Optimization problem formulation

With the application of optimization theory, the energy efficiency based joint cell selection and power allocation problem can be formulated as

$$\max_{\beta_{ij},P_{ij}}\sum_{i=1}^{M}\sum_{j=1}^{N}\beta_{ij}\eta_{ij}\text{s. t. }\ \text{C1: }\ \beta_{ij}\in\{0,1\}\text{C2: }\ P_{ij}\ge 0\text{C3: }\ \sum_{j=1}^{N}\beta_{ij}\le 1\text{C4: }\ \sum_{i=1}^{M}\beta_{ij}\le 1\text{C5: }\ \beta_{ij}=0,\quad \text{if }\ C_j\notin\Phi_i\text{C6: }\ R_i\ge R_i^{\min}\text{C7: }\ \sum_{j=1}^{N}\beta_{ij}P_{ij}\le P_i^{\max}. \tag{15}$$

6. Solution of optimization problem

The optimization problem formulated in (15) involves the coupling of binary optimization and nonlinear fractional optimization, which cannot be solved conveniently using traditional optimization tools. Indeed, it can be shown that the power allocation for any given cell selection strategies can be conducted independently, hence, the joint optimization problem can be equivalently transformed into power allocation subproblem and cell selection subproblem. More specifically, the optimal transmitting power can be designed and the corresponding energy efficiency can be obtained for each cell selection strategy, then the optimal cells which correspond to the maximum energy efficiency of all the users can be selected.

6.1. Iterative algorithm based optimal power allocation scheme

Assuming $\beta_{ij}=1$, i.e., the ith UE selects the jth cell for accessing, the optimal power allocation of the UE can be conducted through solving the following optimization problem:

$$\max_{P_{i,j}}\eta_{i,j}\text{s. t. }\ P_{ij}\ge 0P_{ij}\le P_i^{\max}R_{ij}\ge R_i^{\min}. \tag{16}$$

The optimization problem obtained can be transformed into a convex function and solved using iterative algorithm [19]. To solve the problem, we introduce variable q and denote q^{*} as the maximum energy efficiency of the ith UE when accessing the jth cell, i.e.,

$$q^*=\frac{R_{ij}^*}{P_{ij}^*+P_c}=\max_{P_{i,j}}\frac{R_{i,j}(P_{i,j})}{P_{i,j}+P_c}. \tag{17}$$

It can be proved that the maximum energy efficiency q^{*} is achieved if and only if [19]

$$R_{i,j}(P_{i,j})-q^*(P_{i,j}+P_c)=0 \tag{18}$$

Hence, solving the optimization formulated in (16) is equivalent to solving the following optimization problem:

Table 1
System parameters.

Bandwidth of BSs (MHz)	1, 1, 2, 2, 2
User data rate requirement (Mbps)	1, 2, 0.5, 0.5, 1
Fading distribution	Rayleigh fading with zero mean and unit variance
Channel path loss model	$128.1+27\log(d)$dB d denotes the distance
Noise power	−110 dBm

$$\max_{q,P_{i,j}}R_{i,j}(P_{i,j})-q(P_{i,j}+P_c)\text{s. t. }\ P_{ij}\ge 0P_{ij}\le P_i^{\max}R_{ij}\ge R_i^{\min}. \tag{19}$$

Taking a glance at the optimization problem formulated in (19), it can be realized that for a given energy efficiency q, the problem is transformed into a convex problem of power allocation, which can be solved using Lagrange method, based on which the energy efficiency q can be updated. The process is repeated until the convergence condition is met, then the optimal energy efficiency and the optimal power allocation scheme can be achieved.

The process for solving locally optimal energy efficiency and transmit power alternatively can be conducted by an iterative algorithm, the workflow of which can be expressed briefly as follows: start with an initial value of q, the locally optimal P_{ij} can be obtained through solving the power allocation subproblem, then q is updated based on $q=\frac{R_{ij}}{P_{ij}+P_c}$. For the updated q, the power allocation subproblem can be resolved to obtain updated P_{ij}, the process continues until the convergence condition is met. In Table 1, a summary of the proposed algorithm is presented.

Algorithm 1 illustrates that, in order to get q*, the iterative operation must be undertaken until the algorithm converges. Considering separate iteration, for a given q, the optimization power problem is solved.

Proposed Algorithm I**.** Iterative Resource Allocation Algorithm

1 Set the maximum number of iterations, $U_{\max}$,
 and the maximum tolerance ρ_1
2 Set the energy efficiency q=0 and iteration index u=0
3 **repeat** Main Loop
4 For a given q, solve for P'_{ij}
5 **if** $R_{ij}(P'_{ij})-q'(P'_{ij}+P_c)\le\rho_1$
6 Convergence=**true**
7 **return** $P_{ij}^*=P'_{ij},\ q^*=\frac{R_{ij}(P_{ij}^*)}{P_{ij}^*+P_c}$
8 **else**
9 **set** $q=\frac{R_{ij}(P'_{ij})}{P'_{ij}+P_c}$ and $u=u+1$
10 Convergence=**false**
11 **end if**
12 **until** Convergence=**true** or $u=U_{\max}$

6.2. Lagrange method for solving locally optimal power

For a given q, the power allocation subproblem in (19) can be transformed into the problem below:

$$\max_{P_{ij}}R_{ij}-q(P_{ij}+P_c)\text{s. t. }P_{ij}\ge 0P_{ij}\le P_i^{\max}R_{ij}\ge R_i^{\min}. \tag{20}$$

We use the Lagrange approach to solve the above optimization problem. The Lagrange function can be expressed as:

$$L(P_{ij},\lambda,\nu)=R_{ij}-q(P_{ij}+P_c)-\lambda(P_{ij}-P_i^{\max})-\nu(R_i^{\min}-R_i) \tag{21}$$

where λ and ν are the Lagrange multipliers correlating to both constraints of transmission power and data rate. The Lagrange dual problem can be obtained by:

$$\min_{\lambda,\nu}\max_{P_{ij}} L(P_{ij}, \lambda, \nu)\}\text{ s. t. } \lambda, \nu \geq 0. \tag{22}$$

The above dual problem can be solved by optimizing the transmitting power for a fixed set of Lagrange multipliers, and updating the Lagrange multipliers iteratively. For given Lagrange multipliers λ and ν, we can find the locally optimal power allocation strategy:

$$P_{ij} = \left[\frac{(1+\nu)B_j}{(q+\lambda)\ln 2} - \frac{\sigma^2}{h_{ij}}\right]^+ \tag{23}$$

where $[z]^+ = \max\{0, z\}$. Using the gradient method, we update the Lagrange multipliers:

$$\lambda(t+1) = \lambda(t) - \epsilon_1(t)(P_i^{\max} - P_{ij}) \tag{24}$$

$$\nu(t+1) = \nu(t) - \epsilon_2(t)(R_{ij} - R_i^{\min}) \tag{25}$$

where ϵ_1 and ϵ_2 are stepsize. The proposed Lagrange dual method based power allocation algorithm is shown in Algorithm 2. Until convergence is achieved, the iteration process over Lagrange multipliers keeps repeating.

Algorithm II. Lagrange Dual Method Based Power Allocation Algorithm

1 Set the maximum number of iterations, $t_{\max}$, and the maximum tolerance ρ_2
2 Initialize the Lagrange multipliers λ, ν for t=0
3 **repeat** Main Loop
4 Obtain the power allocation strategy $P_{ij} = \left[\frac{(1+\nu(t)B_j)}{(q+\lambda(t))\ln 2} - \frac{1}{h_{ij}}\right]^+$
5 Update the Lagrange multipliers:
$\lambda(t+1) = [\lambda(t) - \epsilon_1(P_{ij} - P_i^{\max})]^+$
$\nu(t+1) = [\nu(t) - \epsilon_2(R_i^{\min} - R_{ij})]^+$
6 **if** $|\lambda(t+1) - \lambda(t)| + |\nu(t+1) - \nu(t)| \leq \rho_2$
7 Convergence=**true**
8 return $P_{ij}^* = P_{ij}$
9 **else**
10 $t = t + 1$
11 **end if**
12 **until** Convergence=**true** or $t = t_{\max}$

6.3. Optimal cell selection subproblem

Given P_{ij}^*, the optimal cell selection problem can be solved, for convenience, we let:

$$\eta_{ij}^* = \frac{R_{ij}(P_{ij}^*)}{P_{ij}^* + P^c}. \tag{26}$$

The optimal cell selection problem can then be expressed as

$$\max_{\beta_{ij}} \sum_{i=1}^{M}\sum_{j=1}^{N}\beta_{ij}\eta_{ij}^*\text{ s. t. } \beta_{ij} \in \{0, 1\} \sum_{i=1}^{M}\beta_{ij} \leq 1 \sum_{j=1}^{N}\beta_{ij} \leq 1. \tag{27}$$

Typically the optimization problem formulated in (27) is a linear binary matching problem. Viewing cell selection constraints of UEs, this optimization problem can be expressed as an optimal matching problem in bipartite graph and can then be solved by the usage of the algorithms such as the K-M algorithm.

The application of the K-M algorithm is preceded by the presentation of some definitions and a theorem.

Complete bipartite graph: a graph $G = (V; E)$ which consists of a set V of vertices and a set E of pairs of vertices called edges, with V being divided into two disjoint and non-empty sets, X and Y, i.e., $V = X \cup Y$, and every edge in E, i.e., $\forall\ e \in E$ joins one vertex in X to another vertex in Y and no edge connects two vertices of the same set.

Weighted complete bipartite graph: a graph in which the edge connecting X and Y has a non-negative weight $w(x, y)$.

Perfect matching (PM) and maximum matching: A matching K of graph $G = (V; E)$ is defined as a subset of E, i.e., $K \subseteq E$. K is a PM if every vertex is adjacent to some edges in K. A matching K of graph G is a maximum matching if it contains the maximum number of edges, i.e., no other matching K' exists such that $|K'| > |K|$, where $|K|$ denotes the size of the matching K which is equivalent to the number of edges in K.

Feasible vertex labeling: a real valued function l such that for all $x \in X$ and $y \in Y$, $l(x) + l(y) \leq w(x, y)$.

Equality sub-graph (with respect to l): If l is a feasible labeling, let G_l denote a sub-graph of G, if the condition $l(x) + l(y) = w(x, y)$ is met, then G_l is called the equality sub-graph with respect to l.

Theorem: If l is a feasible labeling of G, and K is a PM of X to Y with $K \subseteq G_l$, then K is an optimal assignment from X to Y. Thus, the problem of finding an optimal assignment is reduced to the problem of finding a feasible vertex labeling whose equality sub-graph contains a PM from X to Y.

A weighted complete bipartite graph G with a partition $G^0 = (X, Y; E)$ is formulated in an attempt to solve the problem of optimal cell selection, where X denotes the set of UEs, i.e., $X = [\text{UE}_1, \text{UE}_2, \ldots, \text{UE}_M]$, whiles Y denotes the set of cells, that is, $Y = [\text{C}_1, \text{C}_2, \ldots, \text{C}_N]$. In the weighted complete bipartite graph, the definition of the weight of the edge $E(\text{UE}_i, \text{C}_j)$ is expressed as:

$$w(\text{UE}_i, \text{C}_i) = \eta_{ij}^*. \tag{28}$$

The steps for solving the optimal cell selection subproblem based on the K-M algorithm can be described as follows:

(1) Start with an arbitrary feasible vertex labeling l, determine G_l^0, and choose an arbitrary matching K in G_l^0.
(2) If K is a maximum matching for G, then K is optimal and the optimization problem is solved. Otherwise, a labeling X having not being allocated by the distribution K is selected in G_l^0. Set $S = X$ and $T = \Phi$, which denotes the empty set.
(3) Let $N_{G_l^0}(S)$ denote the collection of points which connect with S in G_l^0. If $N_{G_l^0}(S) \neq T$, go to step (2). Otherwise, $N_{G_l^0}(S) = T$. Find $\Delta = \min\{l(x) + l(y) - w(x, y)|x \in S, y \in Y - T\}$.
(4) Construct a new labeling l' by:

$$l' = \begin{cases} l(x) - \Delta, & x \in S \\ l(x) + \Delta, & x \in T \\ l(x). & \text{otherwise} \end{cases}$$

The process continues until an equal sub-graph consisting a complete match is obtained.

7. Numerical results

In this section, we conduct numerical simulation, examine the performance of the proposed scheme and compare with other previously proposed schemes, including the scheme proposed in [17] and random cell selection scheme. The scheme proposed in [17] aims to maximize the utility function defined as the logarithm function of user data rate. On the other hand, the random cell selection scheme selects the accessing cell for UEs at random. In our simulation, we consider a HetNet scenario consisting of 5 cells with each cell having one BS. The number of UEs is also chosen as 5. We assume that all BSs and UEs are located in a rectangular region with the size being 100 m x 100 m. We consider that the position of all BSs is fixed while we randomize that of

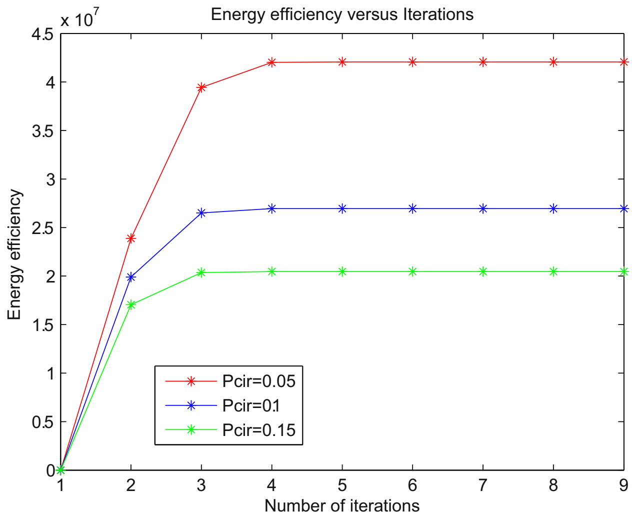

Fig. 2. Energy efficiency versus the number of iteration.

the UEs. The summary of other simulation parameters used in the simulation are provided in Table I. We average the simulation results over 1000 independent adaptation processes. Different realization of the positions of the UEs in each adaptation process is performed.

Fig. 2 shows the energy efficiency of the UEs versus the number of iterations obtained from the proposed algorithm. For comparison purposes, we examine the results for different circuit power of UEs of which the maximum transmitting power P^{max} is chosen as 0.2 W. From the figure, we can see that the energy efficiency converges within a small number of iterations for the three cases. Comparing the results obtained from different circuit power, we can see that the energy efficiency of the UEs decreases with the increase of the circuit power.

Fig. 3 shows the energy efficiency versus the maximum transmitting power of UEs, i.e., P^{max}, for different number of UEs. The circuit power is chosen as 0.05 W. For given P^{max}, we conduct the proposed scheme and the scheme proposed in [17], respectively. Based on the obtained cell selection and power allocation strategies, the energy efficiency of the UEs can be examined and is plotted in the figure.

It can also be seen from the figure that for small P^{max}, the energy efficiency increases with the increase of P^{max}, indicating that a higher maximum power threshold is desired for achieving the maximum energy efficiency. However, as P^{max} reaches a certain value, the energy

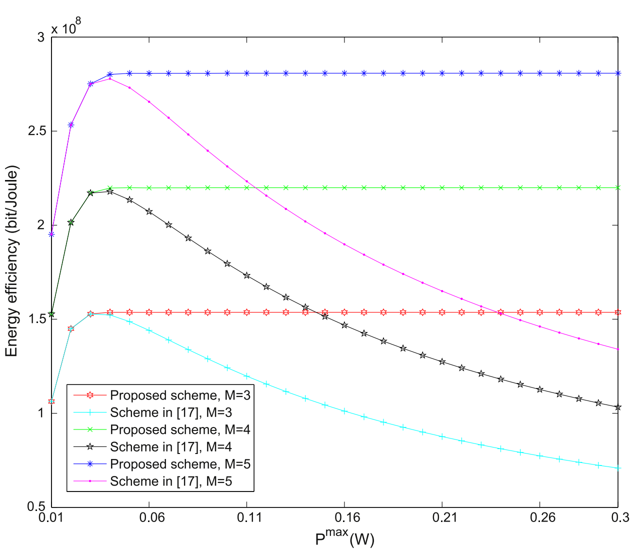

Fig. 3. Energy efficiency versus the maximum transmission power (different number of UEs).

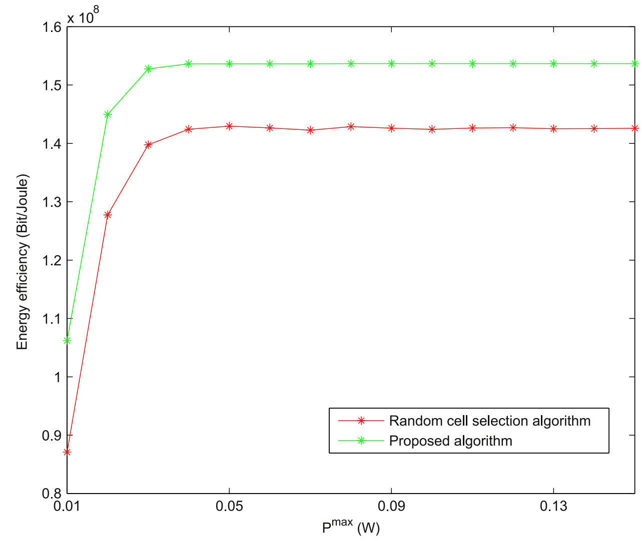

Fig. 4. Energy efficiency versus the maximum transmit power (different cell selection algorithms).

efficiency obtained from the proposed scheme becomes a constant which no longer varies with the increase of P^{max}. This is because the transmit power being less than P^{max} has resulted in the optimal energy efficiency. However, the energy efficiency obtained from the scheme proposed in [17] begins to decrease after reaching the maximum value. The reason is that the scheme proposed in [17] aims to maximize the utility function defined as the logarithm function of user data rate, which requires larger transmit power, resulting in lower energy efficiency. Comparing the curves obtained from the two algorithms, we can see that the proposed scheme outperforms the schemes proposed in [17]. It can also be seen from the figure that the secrecy energy efficiency increases with the increase of user number.

In Fig. 4 we plot the energy efficiency versus the the maximum transmitting power of UEs. The circuit power is chosen as 0.05 W and the number of UEs is chosen as 3 in plotting the figure. To plot both curves, we first apply energy efficiency maximization based power allocation scheme to obtain the optimal transmit power of UEs, then for given power allocation strategies, we conduct both the proposed K-M algorithm based cell selection algorithm and random cell selection algorithm. Comparing the results obtained from the two algorithms, we can see that the proposed algorithm offers better performance in comparison with the random cell selection algorithm. This is because our proposed algorithm aims of maximizing the secrecy energy efficiency, while random user association algorithm determines user association strategies randomly, thus cannot guarantee performance optimization.

To compare the performance of the proposed scheme, we plot the results obtained from the proposed scheme based on K-M algorithm, and those obtained from the proposed scheme in [17] and random choice algorithm. It can be seen that the proposed scheme offers a better performance in comparison with both the proposed scheme in [17] and random choice algorithm.

8. Conclusion

In this paper, we jointly study cell selection and power allocation problem of UEs in a HetNet comprised of multiple heterogeneous cells. To achieve energy efficient data transmission, the problem of joint cell selection and power allocation is formulated as a constrained sum energy efficiency maximization problem. We solve the formulated optimization problem for both single user case and multi-user case. For both cases, through transforming the optimization problem equivalently into two subproblems, i.e., power allocation subproblem and cell selection subproblem, and applying iterative method and the K-M algorithm to solve the two subproblems respectively, the optimal cell selection and power allocation strategies are obtained. Numerical results demonstrate that the proposed algorithm offers higher energy efficiency compared with previously proposed algorithms.

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