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Two-Dimensional Resource Pattern Optimization for Interference Avoidance in Heterogeneous Networks

Peng Liu, Jiandong Li Senior Member, Kan Wang, and Hongyan Li Member

Abstract

Interference management for heterogeneous networks (HetNets) is a research highlight in recent years; one effective method is interference avoidance by resource allocation. Typical resource allocation methods are arranging orthogonal resources between macrocell and femtocells such as in frequency domain in inter-cell interference coordination (ICIC) or time domain in enhanced ICIC (eICIC). However, wireless channels experience time-frequency fading appealing for a two-dimensional resource allocation scheme. By optimizing the resource pattern based on variable channel conditions, plus the introduction of group lasso term, our scheme exploits channel variations in both time and frequency domains and in addition avoids the interference. By grouping the resources in our optimization model, our scheme is flexible and robust against heavy bursty traffic. It is also lightweight in terms of coordination overhead and completely distributed, making it suitable for standard Long Term Evolution (LTE) procedure. Extensive simulations investigate the effect of coordination period and group number on different performance metrics and the effectiveness of our proposed method compared with sole frequency domain and time domain resource allocation approaches.

Index Terms

resource allocation, interference avoidance, HetNets, eICIC, group lasso, pattern optimization

I. INTRODUCTION

Femtocell base stations (FBSs) are low-power nodes to provide high throughput and customized services; together with macrocells they form heterogeneous networks (HetNets). In addition to its small size, low cost and plug-and-play features, femtocell is a big thing in both existing and future mobile communications. Unfortunately, it challenges the interference...
management since femtocell networks tend to be large-scale and self-organized [1]. In a large-scale or dense case, macrocell users (MUEs) may suffer aggregated interference from surrounding FBSs, which complicates interference issues.

The major reason is that macrocell base station (MBS) determines MUEs’ current resource usage based on their channel qualities in the last time slot. Hence, the victims of MUEs have no knowledge of the current resource usage of their nearby femtocells unless we specify interference management techniques. Admittedly, if the information (e.g., traffic load and channel state) of all the network nodes is available, we can jointly optimize all the data to avoid interference or implement real-time cooperation between cells [2]. However, FBS directly plugs into an IP-based wireline backhaul network, where, unlike traditional X2 interface, delay cannot be predicted readily—typically from a few milliseconds to 100s of milliseconds [4]—making the real-time information exchange impossible.

3GPP Technical Report [5] categorizes HetNet interference issues in two types: cross-tier interference (interference between macrocell and femtocells) and co-tier interference (interference among femtocells). In this paper, we only emphasize cross-tier interference problem in the downlink transmission mode.

1Resource usage message can be delivered in user measurement report over uplink control channel [3].
To address cross-tier interference challenge, a typical policy is to isolate some resources from offensive femtocells and meanwhile the victims of MUEs have a prior knowledge of those interference-free resources. Early cross-tier interference avoidance methods focused on spectrum resources, e.g., partial frequency reuse (PFR) recommended in release 8 of the Long Term Evolution (LTE) specification. As illustrated in Fig.1 (a), offensive femtocells are only allowed to access a fraction of frequency bandwidth at any given time, which can be selected fixedly [6], randomly [7], or location based [8]. Afterwards, release 10 developed enhanced intercell interference coordination (eICIC) technique where time-domain avoidance was highlighted. In particular, almost blank subframes (ABS) are defined within which offensive femtocells keep mute to guarantee the transmission of nearby victim MUEs (Fig.1(b)). Along with the performance assessment of different ABS ratios of eICIC [9], [10], the algorithm to optimize the ratio is an active area of research as well, see for example [11].

On the other hand, wireless channel environments vary in both time and frequency dimensions due to Doppler and multipath effects (see Fig.1(c)). To maximize spectrum utility, FBSs need to regulate their allocation adaptive to the channel variations. Recently, the authors in [12] investigate the two-dimensional resource allocation in HetNets and propose a two-timescale hierarchical radio resource management scheme. The long term control only involves the large scale fading, while the short term control is adaptive to the local channel state information. They focus on macro-pico scenario in which case macrocell isolates some resources for the picocells under the coverage, while, in our interested macro-femto case, offensive FBSs optimize their resource patterns individually. During the decision-making of the controls in [12], traffic dynamics are not taken into account, which provides no robustness against bursty traffic. In addition, a central design is not suitable for self-organized femtocell structure.

The purpose of this paper is to design a resource allocation scheme to avoid cross-tier interference, exploit channel variations in both time and frequency domains and as well maintain flexibility (i.e. robust against bursty traffic), and enable it in a completely distributed manner to fit for macro-femto scenario. Helped by the introduction of group lasso term in our optimization model (elaborate later), interference is avoided through restricting the resource usage of femtocells. The reason we address dynamic traffic is the fewer number of users in femtocells than that in macrocell, which may incur more traffic fluctuations in the eyes of FBSs. Such a property requests the resource allocation scheme robust against bursty traffic [14], [19]. To resolve this
issue, we divide resources into several groups each of which consists of a chunk of continuous resource blocks (RBs, the minimum assignable resource in LTE, see Fig 1(b)). Deciding which groups to use rather than specific RBs is more flexible and hence robust against bursty traffic.

Developed by Zhu and Wang [15]–[18], the original idea of chunk-based resource allocation is to mitigate the overhead and complexity in the single subcarrier-based allocation (single RB-based herein). First in [15], bit-error-rate (BER) constraint based allocation is proposed and shown to outperform signal-to-noise ratio (SNR) based allocation. They design a joint chunk, power and bit allocation approach in single-cell Orthogonal Frequency Division Multiple Access (OFDMA) systems in [16] and further apply chunk-based resource allocation in multi-cell scenario [18] and high speed train systems [17]. Besides these merits, we also highlight the robustness of grouping RBs (chunk-based) against bursty traffic.

For ease of understanding, in the sequel, we specify the resource pattern as the set of available RB groups for a certain FBS, and resource pattern optimization (PO) as the decision-making procedure for determining the resource pattern. In addition, the overall procedure for avoiding cross-tier interference is called interference avoidance scheme. In fact, no matter frequency resource isolation, time-domain subframe muting or their combination, any of them can be regarded as a particular form of resource pattern optimization. Resource pattern indicates users to access which RBs at each time instant.

FBSs locally optimize the resource pattern concerning dynamic traffic and channel variations, and update the set of their available RB groups in every \( T_c \) time slots. For MBS, once presetting \( T_c \) and the pattern updating time instants (denoted by \( \{ T_{c,t} \} \) hereafter), plus knowing the specific set of available RB groups of nearby offensive femtocells from victim MUE’s measurement report over uplink control channel [3], the cross-tier interference can be avoided. Note that obtaining user measurement report with respect to channel conditions is standard LTE procedure that does not bring coordination overhead.

Overall, the contributions of this paper can be summarized as follows:

- We propose a lightweight (in terms of coordination overhead) and completely distributed scheme to avoid cross-tier interference in HetNets.

\(^2\)Generally speaking, any two-dimension resource usage can be called a resource pattern. We herein specify the resource pattern simply for the purpose of ease of understanding and illustration.
• By grouping the resources, our approach provides flexibility and robustness against bursty traffic. In addition to introducing group lasso term into the pattern optimization model, our approach can exploit channel variations and as well avoid interference.

• Block Coordinate Decent (BCD) [20] algorithm is utilized to solve a sub-problem in PO with provable fast convergence speed and low complexity.

The rest of this paper is outlined as follows. Section II introduces the system model and the interference avoidance scheme. Inherent pattern optimization problem and the corresponding approach are elaborated in Section III, along with the guidance for practical realization. Extensive numerical simulations are presented in Section IV, where we evaluate the implications of the key design parameters and compare our proposed method with sole frequency domain and time domain approaches. Finally, we conclude this paper in Section V.

II. SYSTEM MODEL AND INTERFERENCE AVOIDANCE SCHEME

A. System Model

We consider a two-tier HetNet, where a macrocell coexists with $F$ femtocells. We integrate all base stations in one set $\mathcal{B} = \{0, 1, 2, \ldots, F\}$ in which 0 indicates MBS and others represent FBSs. Concern an OFDMA system, where the minimum assignable time-frequency resource is RB, indexed by $k \in \mathcal{K} = \{1, 2, \ldots, K\}$. RBs are divided into $G$ groups, and let $g \in \mathcal{G} = \{1, 2, \ldots, G\}$ be the index of groups and $\mathcal{G}_g$ be the set of RBs in the $g$-th group. FUEs are able to access all the channels and the groups do not overlap, i.e., $\bigcup_{g=1}^{G} \mathcal{G}_g = \mathcal{K}$ and $\mathcal{G}_g \cap \mathcal{G}_{g'} = \emptyset$, $\forall g \neq g'$.

We also define resource pattern for femtocell $i$ as a set of resource groups $\Omega^{(i)}$. Two timescales are involved in this paper. Let $T_c$ denote the pattern updating period and $T_s$ denote time slot which is the minimum MAC scheduling interval defined in LTE, respectively. The time instants of updating pattern and time slots are indexed by $\{T_{c,t}\}$ and $\{T_{s,t}\}$.

All of three significant factors in a typical radio link, path loss, shadowing, and multipath time-varying fading, are taken into account. Such that radio link can be modeled as follows.

$$L(\text{dB}) = C_1 + C_2 \log(d) + X_s + X_t,$$

where, $C_1$ and $C_2$ are constant path loss factors, and $d$ is the distance between the transmitter and the receiver. $X_s$ accounts the effect of shadow fading. Besides, frequency domain variations due to multipath effect is modeled as a Rayleigh fading, and time-varying fading is modeled...
as a multi-tap filter, respectively. Time-frequency fading is jointly characterized in $X_t$. Channel gain between two nodes can be computed by $h = 10^{L/10}$. Moreover, we assume that channel gain remains constant within RB but different across RBs.

The signal-to-interference-plus-noise ratio (SINR) of the $k$-th RB of user $u$ associated to the $i$-th femtocell is denoted by $\gamma_{k,u}^{(i)}$. Since herein only average channel conditions of overall users rather than a particular user are used for optimizing resource pattern, we omit $u$ for brevity, remaining that

$$\gamma_k^{(i)} = \frac{p_k^{(i)} |h_k^{(i)}|^2}{IF_k^{(i)} + IM_k^{(i)} + N_0} = \alpha_k^{(i)} p_k^{(i)},$$

by setting $\alpha_k^{(i)} = \frac{|h_k^{(i)}|^2}{IF_k^{(i)} + IM_k^{(i)} + N_0}$, where $p_k^{(i)}$ and $h_k^{(i)}$ are the transmit power and channel gain from the associated $i$-th FBS in RB $k$. The interference consists of two components, from other femtocells ($IF_k^{(i)}$) and macrocell ($IM_k^{(i)}$). The thermal noise power is denoted by $N_0$, which is assumed to be a constant. $B_k$ denotes the bandwidth of RB $k$. User rates are the summation of all rates in the allocated RBs, e.g., user rates of femtocell $i$ is given by

$$R^{(i)} = \sum_{k \in K} B_k \log(1 + \gamma_k^{(i)}).$$

Note that the expressions of MUEs’ SINR and rates are similar to (2) and (3) expect that $\{\gamma_k^{(i)}\}$ and $\{R^{(i)}\}$ are replaced by $\{\gamma_{k,u}^{(0)}\}$ and $\{R_u^{(0)}\}$.

Traffic is classified according to QoS class identifier (QCI) in the LTE Technical Specification [21], which is a reference scalar to a specific packet forwarding behavior (e.g. packet loss rate, packet delay budget). The services of QCI 1-4 are applicable to conventional voice, conventional video, buffered streaming, or real-time gaming; QCI 5-6 apply to IP multimedia signaling or live streaming; QCI 7-9 apply to file sharing, email, P2P, or Web [22].

### B. Interference Avoidance Scheme

The interference avoidance scheme is described in Fig.2. At the time instants $\{T_{c,t}\}$, FBSs ($i$) individually perform PO to determine which groups of RBs can be used in the following time slots, which locally obtains the optimal without coordination between cells\(^3\). This procedure

\(^3\)PO can be further optimized considering the cooperation among femtocells. It is out of the scope of this paper since we only focus on cross-tier interference issue.
jointly exploits channel variations and considers dynamic traffic. MBS (0) obtains the results of PO \{\Omega^{(i)}\} through the speculation from user measurement reports of the associated users over uplink control channel [3]. Once knowing \{\Omega^{(i)}\}, MBS schedules the corresponding victim users to the interference-free RBs. As taking channel conditions and users’ traffic into account, PO is a decision-making procedure with input \((\mathbf{h}^{(i)}, \mathbf{R}^{(i)})\) and output \(\Omega^{(i)}\) for all femtocell \(i \in \mathcal{B}\), where \(\mathbf{h}^{(i)} = [h_1^{(i)}, h_2^{(i)}, ..., h_K^{(i)}]\) is the channel condition vector of femtocell \(i\).

At the moment of optimizing the resource pattern \(\{T_{c,t}\}\), channel conditions in current time instants\(^4\) are employed to decide available resource groups for the following time slots before \(\{T_{c,t+1}\}\). Such an arrangement is similar to comb-type pilot based channel estimation [23], i.e., insert a pilot in the first time slot of a predefined time period. Within the interval, channel conditions are estimated by using the channel information at pilot channels. The length of the predefined time period is associated with the accuracy of channel estimation. Similar to [23], we also evaluate the implication of \(T_c\) on system performance in the simulation.

Moreover, we are unable to know users’ traffic requirement of the upcoming time slots, and hence a predicted value \(\hat{\mathbf{R}}^{(i)}\) is introduced. Indeed, it will be more accurate by utilizing advanced methods such as auto-regressive model to estimate the average throughput according to the past values [24], [25]. For brevity, we simply make a linear combination of the total demands during last \(T_c\) and the demand of the current time slot. Based on that, the input of pattern optimization becomes \((\mathbf{h}^{(i)}, \hat{\mathbf{R}}^{(i)})\) and PO is formulated by

\[
(\mathbf{h}^{(i)}, \hat{\mathbf{R}}^{(i)}) \rightarrow \Omega^{(i)}.
\]  (4)

\(^4\)Strictly, they should be from the last time slot. Since there exists at most one slot lag, we do not distinguish them for brevity.
Once knowing \( \{\Omega^{(i)}\} \), FBSs will allocate those RBs within \( \{\Omega^{(i)}\} \) to their associated users in \([T_{c,t}, T_{c,t+1}]\). It is a typical MAC scheduling procedure in LTE, and some well-known alternatives can be applied (e.g., proportionally fair scheduling [26] and throughput to average [27]). To capture traffic classification in LTE, we employ an approach similar to [28]. Packets with QCI 1-4 are served in the order of their priorities, and sequentially allocated the best RBs until their buffers are empty. The remaining RBs are allocated to the packets with QCI larger than 4 using proportionally fair algorithm.

III. PATTERN OPTIMIZATION APPROACH AND PRACTICAL IMPLEMENTATION

A. Pattern Optimization Approach

Recall that one purpose of pattern optimization is to exploit channel variations. We obtain this by leveraging minimizing total transmit power in the optimization model. Due to adding an internal process, the decision-making procedure (4) becomes \((h^{(i)}, \hat{R}^{(i)}) \rightarrow p^{(i)} \rightarrow \Omega^{(i)}\). We call the first inner transformation sub-PO1 and the second inner transformation sub-PO2, respectively.

Channel variations can be exploited by formulating an optimization problem of minimizing total transmit power with rate requirement constraints; the solutions can be obtained by pooling power in the good conditioned channels using water-filling method [30]. However, this formulation does not provide interference avoidance-restricting the resource usage of offensive femtocells. To enable interference avoidance, we add a group lasso term in the objective function. Mathematically, it results in the allocated resources not only sparse but also group sparse [13]. That is, the components within a resource group are more likely to be all zeros [29].

We omit superscript \((i)\) for brevity since the decisions are made by FBSs individually. Thus, the sub-PO1 can be expressed as

\[
\text{sub-PO1: } \min_p F(p) \triangleq \sum_{k \in \mathcal{K}} p_k + \lambda \sum_{g \in \mathcal{G}} \|p_g\|_2 \tag{5a}
\]

subject to \( \mathcal{R} \geq \hat{\mathcal{R}} \),

\[
p_k \leq p^\text{max}_k, \quad \forall k \in \mathcal{K}, \tag{5b}
\]

where, \( p \) is a \( K \times 1 \) vector whose component \( p_k \) denotes the user’s transmit power at RB \( k \), e.g., \( p = (5, 0, 3, 0, ..., 1) \) represents the user’s transmit power at the first RB is 5, the third is 3, etc.
The objective function is the combination of minimizing the total power (the first term) and group lasso term (the second term) which is used to account for fewer RB groups. $p_g$ denotes a vector consisting of $p_k$ for $k \in G_g$. Moreover, the constraints are rate requirements (5a) and maximum power cap constraints (5b), respectively. Note that we assume that the problem is always feasible in that $\hat{R}$ is the predicted average user throughput by using historical information which must lie in the feasible region$^5$.

Employing group sparsity architecture or $l_2/l_1$ norm architecture in the objective function enforces the solutions of sub-PO1 occupying fewer groups instead of simply using less total power. $\lambda$ is a tuning parameter to control the degree of group sparsity (i.e., the number of available RB groups). In another way, femtocells can be benefited by obtaining more available RB groups with small $\lambda$, but on the contrary, a large $\lambda$ restricts the usage of RBs for femtocells such that the victim MUEs have more opportunities to be allocated the channels with better conditions.

![Fig. 3. Different allocation results with $\lambda = 0$ (top), $\lambda = 1$ (middle) and $\lambda = 5$ (bottom); the black bar represents the allocated RBs and the grey bar represents the RB which is used in above bar chart but not used currently. In the top, an allocation example when $\lambda$ is set to 0 (no group sparse consideration) is shown, and $\Omega = \{1, 2, 3, 4, 5\}$ accounts for the whole groups. With the increase of $\lambda$, $\lambda = 1$ and $\lambda = 5$ respectively, the size of $\Omega$ shrinks from 4 ($\Omega = \{1, 2, 3, 5\}$) to 3 ($\Omega = \{1, 3, 5\}$), which means the increase of the degree of group sparsity.]

Before elaborating the algorithm, we first illustrate the function of $\lambda$ in Fig.3, where 50 RBs are evenly divided into 5 groups. In Fig.3 (top), a typical allocation result when $\lambda$ is set to 0 (no group sparsity consideration) is shown, and $\Omega = \{1, 2, 3, 4, 5\}$ accounts for the whole

$^5$Infeasibility happens when the channel in the current slot is extremely bad and the traffic in the past slots is heavy. However, we investigate indoor femtocell scenario, in which case the above-mentioned situation scarcely appears.
groups. With the increase of $\lambda$ ($\lambda = 1$ and $\lambda = 5$ respectively), the size of $\Omega$ shrinks from 4 ($\Omega = \{1, 2, 3, 5\}$) to 3 ($\Omega = \{1, 3, 5\}$), which means the increase of the degree of group sparsity and hence the profit of MUEs. Therefore, $\lambda$ provides a tradeoff between the performance of macrocell and femtocells.

Due to the group lasso term, sub-PO1 is nonsmoothly convex with nonlinear constraints. Traditional optimization algorithms such as interior-point methods and active set method are not applicable to the nonsmooth case. We introduce Block Coordinate Decent (BCD) based algorithm which is motivated by the fact that the objective function of sub-PO1 is smooth and convex only considering a particular group (when fixing the variables in other groups). This observation encourages us to design the algorithm iterating alternatively, group by group, to deal with a simple smooth convex problem in each iteration, and ultimately converging to a global limit point.

BCD approach iterates partial points in each time of Gauss-Seidel type and does iterative process in a cycle way. The details are elaborated in Algorithm 1, where $n$ indicates iteration index, $(\cdot)[n]$ means the value of a variable in the $n$-th iteration, and $\epsilon$ is a predefined constant to terminate the algorithm. In every outer iteration, BCD implements $G$ inner iterations (step 3-step 5). During the $g$-th inner iteration of a certain outer iteration, the objective function is called the groupwise function

$$F_g(p_g) = \sum_{j \in G_g} p_j + \lambda \sqrt{\sum_{j \in G_g} p_j^2},$$

which is the same with the one in sub-PO1 except only considering the variables in $G_g$. In Algorithm 1, $P_g$ represents the feasible set of sub-PO1 in the $g$-th group when the variables in other groups are fixed, that is

$$P_g \triangleq \{ p_g : (p_1, \ldots, p_{g-1}, p_g, p_{g+1}, \ldots, p_G) \in P \},$$

where $P$ is the feasible set of sub-PO1. Due to the Gauss-Seidel fashion, $P_g$ in the $n$-th iteration will be

$$P_g[n] \triangleq \{ p_g : (p_1[n], \ldots, p_{g-1}[n], p_g, p_{g+1}[n-1], \ldots, p_G[n-1]) \in P \}$$

We call the subproblem in the inner iteration to find the solutions to minimum groupwise function over the convex set $P_g$ Inner Problem. Inner Problem can be efficiently solved through
Algorithm 1: Block Coordinate Descent based method for solving sub-PO1

1: **Initialization:**
   \[(\mathbf{p}_1[-1], ..., \mathbf{p}_G[-1]) = (\mathbf{p}_1[0], ..., \mathbf{p}_G[0]) = \mathbf{0}\]
2: **for** n=1, 2, ... **do**
3:     **for** g=1, 2, ... ,G **do**
4:         Call **Algorithm 2** to solve Inner Problem: \[\mathbf{p}_g[n] = \arg\min_{\mathbf{p}_g \in \mathcal{P}_g[n]} F_g(\mathbf{p}_g).\]
5:     **end for**
6:     **if** \[\|\mathbf{p}[n + 1] - \mathbf{p}(n)\|^2_2 \leq \epsilon\] **then**
7:         return \((\mathbf{p}_1[n], ..., \mathbf{p}_G[n])\).
8: **end if**
9: **end for**

bisection. To be specific, we first omit \([n]\) and \(j \in \mathcal{G}_g\) for brevity. Denote by \(\mathcal{R}^-\) the remaining rate requirement, which is given by

\[
\mathcal{R}^- = \hat{\mathcal{R}} - \sum_{j \in \mathcal{K}, j \notin \mathcal{G}_g} B_j \log(1 + \alpha_j p_j). \tag{9}
\]

Then, we define the Lagrangian of Inner Problem as

\[
\mathcal{L}(\mathbf{p}, \beta) \triangleq \sum_{j} p_j + \lambda \sqrt{\sum_{j} p_j^2} + \beta(\mathcal{R}^- - \sum_{j} B_j \log(1 + \alpha_j p_j)), \tag{10}
\]

where, \(\beta\) is the Lagrange multiplier associated with the rate constraint.

If \(p_j^*\) is the points satisfying \(\frac{\partial \mathcal{L}}{\partial p_j^*} = 0\), then

\[
\frac{\partial \mathcal{L}}{\partial p_j^*} = 1 + \lambda p_j^* - B_j \cdot \frac{\alpha_j}{1 + \alpha_j p_j} \cdot \beta = 0.
\]

Thus, the solutions of Inner Problem will meet

\[
p_j^* = \\
\min \left\{ \max \left\{ \sqrt{\frac{B_j \beta}{\lambda} + \left(\frac{\lambda - \alpha_j}{2 \lambda \alpha}\right)^2} - \frac{\lambda + \alpha_j}{2 \lambda \alpha}, 0 \right\}, p_j^{\max} \right\}. \tag{11}
\]

Substituting (11) to (3), we get a one-to-one mapping from \(\beta\) to \(\mathcal{R}\), denoted by \(\mathcal{R}(\beta)\). Finding the solutions of Inner Problem can turn to searching \(\beta\) and then compute \(\mathcal{R}(\beta)\) until meeting the rate constraint.
Algorithm 2 Bisection for solving Inner Problem

1: Obtain \( \{ \beta_j \} \) through solving the equation,
\[
\sqrt{\frac{B_j \beta_j}{\lambda}} + \left( \frac{\lambda - \alpha_j}{2 \lambda \alpha_j} \right)^2 = \frac{\lambda + \alpha_j}{2 \lambda \alpha_j}.
\]

2: Pick out the largest \( \beta_l \in \{ \beta_j \} \) meeting \( R(\beta_l) \leq R^- \) and the smallest \( \beta_s \in \{ \beta_j \} \) meeting \( R(\beta_s) \geq R^- \).

3: Do bisection within \( (\beta_l, \beta_s) \) until rate constraint is satisfied. Return \( \{ p^*_i \} \).

Bisection for solving Inner Problem is elaborated in Algorithm 2. More specially, to search \( \beta \), we first determine the searching interval. By doing step 2, we know \( \beta \) must lie between \( \beta_l \) and \( \beta_s \) because \( R(\beta) \) are monotonically increasing with \( \beta \) (see (11) and (3)). Then, we perform bisection within the selected interval until the rate constraint is satisfied (step 3).

The convergence rate of Algorithm 1 is summarized in Theorem 1. According to [20], the complexity of the outer iteration is \( \mathcal{O}(G^2) \). By the observation of Algorithm 2, it will take \( K/G \) (i.e., the number of RBs in each group) steps to find the searching interval. Omitting the complexity of bisection (step 3 in Algorithm 2), the total complexity of Algorithm 1 is \( \mathcal{O}(KG) \) which is proportional to the number of groups instead of the number of RBs.

**Theorem 1.** If sub-PO1 is solved by Algorithm 1, then it converges to a Nash Point\(^6\) \( p^* \), and the rate of convergence is linear, i.e.,
\[
\| p[n] - p^* \|^2_2 \leq C \tau^n, \quad \text{for certain} \quad C > 0, \tau \in [0, 1).
\]

**Proof.** The main idea of proving Theorem 1 is to show that our formulation sub-PO1 satisfies the general convergence framework in [34], where block is replaced by group. First, we learn that sub-PO1 follows the basic proof structure presented in [34]. For one thing, the feasible set of sub-PO1 is block multi-convex in that \( \mathcal{P}_g \) defined in (7) is a convex set. For another, the groupwise objective function (6) is convex.

Next, we prove that sub-PO1 is in accordance with the general convergence framework of BCD method. There are four steps in total:

\(^6\)If \( p^* = (p^*_1, \ldots, p^*_{g-1}, p^*_g, p^*_{g+1}, \ldots, p^*_G) \) satisfies Nash equilibrium condition, i.e.
\[
F(p_1^*, \ldots, p_{g-1}^*, p_g^*, p_{g+1}^*, \ldots, p_G^*) \geq F(p_1^*, \ldots, p_{g-1}^*, p_g^*, p_{g+1}^*, \ldots, p_G^*),
\]
\( \forall p_g \in P_g \), then we call \( p^* \) is a Nash Point.
1) prove the groupwise function (6) is strongly convex;
2) the objective function of sub-PO1 is lower bounded in the feasible set;
3) if $p[0]$ is sufficiently close to $p^*$, then $F'(p[n]) > F'(p^*)$ for all $n \geq 0$;
4) $F(\cdot)$ defined in the objective function of sub-PO1 satisfies the Kurdyka-Lojasiewicz condition (explained later).

A differentiable function $\psi$ defined on a convex set $\mathcal{X}$ is said to be strongly convex [35] if there exists $m > 0$ such that

$$\langle \nabla \psi(u) - \nabla \psi(v), u - v \rangle_{\mathcal{X}} \geq \frac{m}{2} \|u - v\|_2^2$$

(13)

Note that the second term in (6) is a $l_2$ norm with gradient $\nabla F_g(x_i) = \frac{x_i}{\|x\|_2}$ when $x \neq 0$ and 0 otherwise. Without loss of generality, we assume $u_i > 0, v_i > 0$ for all $i$, and hence

$$\langle \nabla F_g(u) - \nabla F_g(v), u - v \rangle_{\mathcal{X}} = \sum_{i=1}^{\left|G_g\right|} \left( \frac{u_i}{\|u\|_2} - \frac{v_i}{\|v\|_2} \right) (u_i - v_i) = \sum_{i=1}^{\left|G_g\right|} \left( \frac{u_i}{\|u\|_2} - \frac{v_i}{\|v\|_2} \right) (u_i - v_i).$$

(14)

Then we obtain

$$\sum_{i=1}^{\left|G_g\right|} \left( \frac{u_i}{\|u\|_2} - \frac{v_i}{\|v\|_2} \right) (u_i - v_i) \geq \sum_{i=1}^{\left|G_g\right|} \frac{(u_i - v_i)^2}{\max\{\|u\|_2, \|v\|_2\}} \geq \frac{1}{\max_{x \in \mathcal{X}} \|x\|_2^2} \|u - v\|_2^2$$

(15)

Setting $m_g = \frac{2}{\max_{x \in \mathcal{X}} \|x\|_2}$, we find $m = m_g$ making (6) satisfy (13). Thus, we complete the first step.

To explain the second condition is trivial since the feasible set is bounded and $p_i$ is limited by $p_i^{\max}$.

When it comes to the third step, it will naturally hold provided that

$$F(p[n-1]) - F(p[n]) > 0, \text{ for all } n$$

Based on Lemma 2.1 in [34], we have

$$F_g(p_g[n-1]) - F_g(p_g[n]) \geq \frac{c_g[n-1]}{2} \|p_g[n-1] - p_g[n]\|_2^2,$$

where $c_g[n-1] > 0$ is a constant, and therefore

$$F(p[n-1]) - F(p[n]) = \sum_{g=1}^{G} (F_g(p_g[n-1]) - F_g(p_g[n])) \geq \sum_{g=1}^{G} \frac{c_g[n-1]}{2} \|p_g[n-1] - p_g[n]\|_2^2.$$
Normally (15) is not equal to 0 unless all \( \{p_i\} \) are 0, which is not included in \( \mathcal{P} \). Hence, the inequality (15) holds strictly and we finish the third step.

To prove the forth condition, we leverage the conclusion in [34]; if \( F(p) \) is a locally strongly convex function, condition 4 is satisfied automatically. A locally strongly convex function means it is strongly convex in a neighborhood \( D \). The \( F_g(p_g) \) is locally strongly convex and 0 is out of its feasible set \( \mathcal{P} \). There always exists a \( m > 0 \) (we can set \( m \) to the minimum \( \{m_g\} \) among all groupwise functions) such that (13) holds. Therefore, our objective function is locally strongly convex and the last condition holds.

Actually, the global convergence feature benefits from the special structure of our problem, i.e., the groupwise convex feature and its feasible set excluding 0.

\[ p_k > \hat{\epsilon}, k \in G_i \Rightarrow G_i \in \Omega. \]

Note that the fairly good alternative of the threshold is \( \epsilon \) (the same with that of termination condition in Algorithm 1). As we have analyzed, some components of the solutions to sub-PO1 will be 0. We use \( p(0) \) to indicate the components in \( p \) being 0 at the optimal. Suppose Algorithm 1 terminates at the \( n \)-th iteration, the residual errors will be \( p(0)[n] \). From (12), we get

\[ \|p(0)[n]\|_2^2 \leq C\tau^n. \]

Then, \( \exists 0 < C_{n-1} \leq C, 0 < C_n \leq C \) making \( \|p(0)[n]\|_2^2 = C_n\tau^n \) and \( \|p(0)[n-1]\|_2^2 = C_{n-1}\tau^{n-1} \).

According to the step 6 in Algorithm 1, we know

\[ |C_{n-1}\tau^{n-1} - C_n\tau^n| = \|p(0)[n-1] - p(0)[n]\|_2^2 \leq \epsilon. \]

From (16) and (17), we derive

\[ \max\{p(0)[n]\} \leq \|p(0)[n]\|_2^2 \leq \frac{\epsilon C\tau^n}{|C_{n-1}\tau^{n-1} - C_n\tau^n|}. \]
Thus, in order to neglect the components should be 0 at the optimal, \( \hat{\epsilon} \) can set
\[
\hat{\epsilon} \geq \frac{\epsilon C \tau}{|C_{n-1} - C_n \tau|}.
\]
(19)

In our simulation (see Fig. 6), the convergence speed of Algorithm 1 is very fast. Therefore, \( \tau \) is next to 0 and \( \hat{\epsilon} = \epsilon \) is sufficient to pick out the resource group.

B. Practical Implementation

In practice, no extra hardware is required in LTE architecture and no extra control signaling is needed to occupy wireless bandwidth. All base stations regardless of MBS and FBSs have a common knowledge of \((\{T_{c,t}\}, T_c, \mathcal{G})\). FBSs update available resource groups \(\{\Omega^{(i)}\}\) in pattern updating time \(\{T_{c,t}\}\) through Algorithm 1. At that time, victim MUEs detect RBs’ qualities and deliver associated messages to MBS in the uplink control channel. Note that it is a standard procedure in LTE standards (refer to [3] for further details). Since MBS has a prior knowledge of \(\mathcal{G}\) (i.e., how to divide resource groups), it can deduce which groups are interference-free. Admittedly, offensive femtocells may experience a light traffic load in \(\{T_{c,t}\}\) and will not occupy all RBs in available groups. It leads to overly optimistic estimate for some victim MUEs. The misinformation can be avoided through enforcing FBSs to transmit power in the RBs belonging to available resource groups in \(\{T_{c,t}\}\) in the practical implementation.

IV. NUMERICAL SIMULATION

A. Simulation Setup

To evaluate our proposed scheme, we conduct extensive snapshot based simulations. In each snapshot, we first fix geographical locations of network nodes, and then last the simulation 10000 time slots (10s in LTE) along with the generation of dynamic traffic and channel variations. To be specific, one MBS is deployed at the center of a \(400 \times 400 \) (m\(^2\)) square. The whole region is divided into 400 blocks \((20 \times 20)\) and one FBS is randomly dropped in each block with a predefined probability (deployment ratio). Only one FUE is assumed to associate to each FBS and can bear all traffic classes. As long as the FBS is active, we also generate a FUE in a random location within this block. MUEs are distributed uniformly within the whole coverage range. Table I lists the system settings which are based on LTE Technique Specifications [32].
TABLE I
SIMULATION SETTINGS

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Assumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inter-site distance</td>
<td>400m</td>
</tr>
<tr>
<td>Number of MUEs</td>
<td>40</td>
</tr>
<tr>
<td>Deployment ratio</td>
<td>0.25</td>
</tr>
<tr>
<td>Total Band</td>
<td>10MHz</td>
</tr>
<tr>
<td>Band of RB</td>
<td>180KHz</td>
</tr>
<tr>
<td>RBs Number</td>
<td>50</td>
</tr>
<tr>
<td>Indoor path loss model</td>
<td>$C_1 = 38.46, C_2 = 20$</td>
</tr>
<tr>
<td>Outdoor path loss model</td>
<td>$C_1 = 15.3, C_2 = 37.6$</td>
</tr>
<tr>
<td>Shadowing standard deviation (dB)</td>
<td>$X_s = 8$</td>
</tr>
<tr>
<td>Max Tx Power FBS</td>
<td>20dBm</td>
</tr>
<tr>
<td>Tx Power per RB of FBS</td>
<td>3dBm</td>
</tr>
<tr>
<td>Tx Power MBS</td>
<td>46dBm</td>
</tr>
</tbody>
</table>

TABLE II
TRAFFIC MODEL

<table>
<thead>
<tr>
<th>Class</th>
<th>Priority</th>
<th>Model</th>
<th>Packet rate (p/s)</th>
<th>Packet length</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class A</td>
<td>1</td>
<td>Period</td>
<td>50</td>
<td>2 Kb</td>
</tr>
<tr>
<td>Class B</td>
<td>2</td>
<td>Poisson</td>
<td>16</td>
<td>400 Kb</td>
</tr>
<tr>
<td>Class C</td>
<td>3</td>
<td>Poisson</td>
<td>3</td>
<td>4 Mb</td>
</tr>
</tbody>
</table>

Once the locations are determined, channel variations and dynamic traffic are generated slot by slot. Specific parameters regarding small-scale fading refer to [31], where MUEs’ and FUEs’ channel variations correspond to the outdoor model and the indoor model, respectively. Traffic model is similar to [19]. As illustrated in Table II, three types of traffic with different profiles are generated. Class A is used to simulate LTE traffic class with QCI 1-4. It generates at fixed period with fixed length and normally requires a strict delay budget less than 200 ms. Class B and Class C correspond to LTE traffic classes with QCI 5-6 and QCI 7-9, respectively. They are Poisson traffic in order to simulate traffic dynamics and different packet lengths, and provide different traffic intensity. For MUEs, only traffic class A is assumed. Although the traffic burst in traffic class A happens periodically, this assumption is more similar to full buffer setting due to large number of MUEs [19].
B. Implications of design parameters

Fig. 4. The effect of different number of groups. (a) CDF of delay of traffic class A from FUEs; (b) CDF of delay of traffic class B from FUEs; (c) CDF of delay of traffic class C from FUEs; (d) CDF of delay from MUEs.

Two key design parameters are number of groups \((G)\) and pattern updating period \((T_c)\). We investigate their implications in Fig.4 and Fig.5 in order.

With different number of groups, there exists a tradeoff between the flexibility of femtocells and the drop probability of MUEs\(^7\). The flexibility stands for the ability of the robustness against traffic burst. We take cumulative distribution function (CDF) of traffic’s delay as performance metric; more flexibility of a setting acts out that its corresponding CDF curve is more inclined to the upper-left side.

Observing two extreme cases in Fig.4, when group’s number becomes 1, the flexibility is the largest and hence the black curve is dominated. However, this setting leaves no available groups for MUE if the traffic load is heavy, thereby causing the largest outage probability. On the other side, there will be no flexibility for femtocells when group’s number is equal to RBs’ number (see the red curve in Fig.4(c)). It is implicit to compare the settings with other number of groups in that the flexibility is not monotonous with the increase of the number of groups, especially

\(^7\)Note that the performance metric in the simulation is the CDF of the delay. It can be, to some extent, transformed to the drop probability. Since traffic class A has a strict delay budget, we can define the drop probability of MUE as the ratio of number of traffic whose scheduling time longer than a predefined delay budget (200 ms) to the total number of traffic.
in Fig.4(c). It is majoraly because that even if we divide more groups (which seems to bias MUEs), it may also be compensated by picking out more number of groups. In the following, we set the number of groups as 10, a relative better setting in our simulation. In practice, this setting can be further optimized through tracking system performance in a relatively long term.

![Graph showing the relationship between drop probability and length of Tc (ms)](image)

**Fig. 5.** The effect of different pattern updating period

For $T_c$, as the channel conditions in the first slot are utilized to determine the groups, a large value will lead to the FBSs to allocate bad conditioned channels and finally result in more power consumption. To verify that, we take the average transmit power of FBSs as the performance metric. Based on the above analysis, the best setting is $T_c = T_s$. On the other hand, it is also the most selfish strategy of femtocells in which case victim MUEs completely do not know femtocells’ channel usage. To evaluate the implications on MUEs, we take drop probability as another performance metric, which is defined as the ratio of number of traffic whose scheduling time longer than a predefined delay budget (200 ms) to the total number of traffic.

Fig.5 shows an obvious tradeoff between the performance of macrocell and femtocells. At the start, the transmit power boosts gradually with the increase of $T_c$ but its increasing rate speeds up after around 200-250 ms. A noticeable fact is that the turning point is close to the theoretical channel coherence time (215 ms) in our employed indoor model\(^8\). A reasonable interpretation is that channel estimation error remains a fairly good accuracy within channel coherence time.

\[^8\text{Channel coherence time can be estimated by } \frac{0.423}{f_m} \text{ [33], where } f_m \text{ denotes maximum Doppler shift. In our employed model, } f_m = 2, \text{ and hence the channel coherence time will be 215 ms}\]
and hence channel allocation, to some extent, maintains the good performance. Another curve is the decrease of drop probability of MUEs as $T_c$ enlarging; larger pattern updating period allows longer interference-free time for MUEs. The sharp variation in the first part can be attributed to the mechanism of interference avoidance procedure. That is, offensive femtocells update their patterns in $T_{c,0}$ and the result is sensed by the nearby victim MUEs in next time slot. Thus, for a victim MUE, the safe time is $[1 + T_{c,0}, T_{c} + T_{c,0} - 1]$ in every $T_c$. The relative safe time will lengthen with the increase of $T_c$ but the increasing rate drops quickly. After around 150 ms, the drop probability lies a low level (below 0.1) and almost remains the same. Based on the above study, we obtain an effective $T_c$ setting range-between two dot-dash lines-to provide a guidance on practical application.

C. Convergence with different turning parameter $\lambda$

![Fig. 6. The convergence of Algorithm 1 with different $\lambda$. When $\lambda = 10$, the curves are more concentrated than the case of $\lambda = 1$, which verifies the group sparse property with large $\lambda$.](image)

As we can see in Fig.6, the convergence rate is extremely fast and only 2 steps are required. Furthermore, when $\lambda = 10$, the curves are more concentrated than the case of $\lambda = 1$ and more RBs’ transmit powers are around 0, which verifies the group sparse property with large $\lambda$.

D. Comparison with other methods

To show the effectiveness, we also compare our interference avoidance scheme with the following two baseline methods, partial frequency reuse (PFR) and time-domain eICIC.
Fig. 7. Comparison with other methods: (a) CDF of delay of traffic class A from FUEs; (b) CDF of delay of traffic class B from FUEs; (c) CDF of delay of traffic class C from FUEs; (d) CDF of delay of MUEs.

- Baseline 1: PFR with ratio 2/3; Offensive femtocells occupy 2/3 fraction of the total number of RBs and leave 1/3 of them to victim MUEs during all simulation time.
- Baseline 2: eICIC with muted pattern 1/3; 1/3 fraction of time slots are muted periodically in every frame (10 ms in LTE).

To make a fair comparison, the ratio of resource isolation is specified such that the CDF of traffic’s delay from MUEs is coincided between three methods. Thus, we can observe the improvement of our proposed method in other curves such as the CDF of traffic class C’s delay from FUEs. Moreover, \( G = 10 \) and \( T_c = 100 \).

As we can see in Fig.7, the gain of our proposed method is considerable especially in heavy traffic case, almost 100% improvement (Fig.7(c)). Such an enhancement is at a slight cost of the performance of traffic class A compared with eICIC (see Fig.7(a)). It is mainly because that traffic class A has the highest priority; when it is generated the packets choose best conditioned RBs and eICIC can provide more options. This may not happen in traffic class B and C since they perform a per-RB based scheduling. Indeed, employed MAC scheduling approach does have an implication on the performance of eICIC and PFR, and we have launched an independent work to qualify this effect. However, it will not affect the dominant property of our proposed method in terms of withstanding the burst of heavy traffic load due to the sufficient exploitation.
Fig. 8. Resource pattern through different schemes. (a) The pattern of channel variations; (b) Resource allocation pattern through our proposed scheme; (c) Resource allocation pattern through Baseline 1; (d) Resource allocation pattern through Baseline 2 of channel fluctuations compared with PRF and eICIC.

E. Example

To give a visual representation of resource allocation results of different schemes, we illustrate channel variations and the corresponding resource patterns in Fig. 8. To be specific, the shading of the color in Fig.8(a) represents the channel conditions of a particular realization in 500 (ms) by 50 RBs, where the brighter color indicates the better channel conditions. It can be obtained through the projection of two-dimensional channel variations in Fig.1(c) to the XOY-plane. The resource pattern of our proposed scheme, PFR and eICIC are listed in Fig.8(b), Fig.8(c) and Fig.8(d), respectively, where blue color marks the RB being occupied. Obviously, our proposed method matches best with time-frequency channel variations. A noticeable time interval is around 180-280 ms. Most of resource patterns of all three methods are blank because nearly no traffic
is generated during that time.

V. CONCLUSION

In HetNets, we design an interference avoidance scheme. Such a method can avoid cross-tier interference, exploit channel variations and withstand the burst of heavy traffic. Moreover, it is a lightweight (in terms of cooperation overhead) and completely distributed method, simply using standard LTE protocol. We investigate the system performance when setting different number of groups and cooperation updating period through extensive simulations. The former can be determined through long-term optimization. The later provides a tradeoff between FUEs and MUEs and the effective operation range is introduced to give a practical guidance. We also compare the CDFs of delays with respect to different traffic classes with other standard suggested approaches (PFR and eICIC) in LTE, which shows the dominate performance of our scheme in terms of providing robustness against traffic burst. Meanwhile, we learn that specific MAC scheduling methods may affect the comparison of time-domain eICIC and PFR, and hence we have launched an independent work to scrutinize it.

REFERENCES


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