Greening Effect of Spatio-Temporal Power Sharing Policies in Cellular Networks with Energy Constraints

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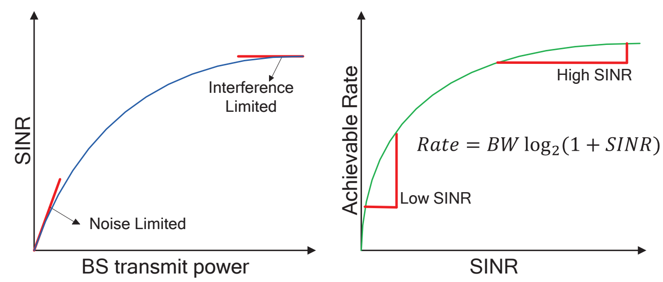
***Abstract*—Greening effect in interference management (IM), a way of enhancing spectrum sharing via intelligent transmit power control, can be achieved by the fact that as BSs moderately reduce their transmit powers, the performance degradation decreases slower than linearly, yet a considerable overall energy saving is expected due to transmit powers' exerting influence on operational power. This paper investigates the impact of different spatial and/or temporal power sharing policies for a given system-wide power budget in IM schemes. We develop an optimization-theoretic IM framework on cellular network greening, from which we first develop four IM schemes governed by different power sharing: no sharing, only temporal sharing, only spatial sharing, and both spatial and temporal sharing. Through extensive simulations, including a real BS deployment in Manchester city, United Kingdom, we obtain the following interesting observations: (i) the gains both from performance and power saving are obtained by adopting the spatial and/or temporal power sharing policies, (ii) tighter greening regulation (i.e., smaller total power budget) leads to higher spatio-temporal power sharing gain than IM gain, (iii) spatial power sharing significantly excels temporal one in terms of power saving, and (iv) higher greening efficiency can be achieved as the cell size becomes smaller.**

***Index Terms*—Greening effect; interference management (IM); power budget; spatial power sharing; temporal power sharing; energy-saving regulations; power allocation; user scheduling; greening efficiency; different cell size;**

I. Introduction

Information and Communication Technology (ICT) is one of the industries consuming a significant amount of energy, reported to amount to about 2-10% of the world-wide energy consumption [2]. In particular, the energy expended on the operation of cellular networks reaches 25% of the total ICT energy consumption [3], where base stations (BSs) are the dominant components consuming 60-80% of total energy usage in the whole cellular networks [2].

In a typical macro BS, the amount of transmit power is in fact low (e.g., 10-20W), compared to the total operational power (e.g., 500-2000W). However, the transmit power exerts substantial influence on the required power for amplifiers, cooling systems, and so on, where the influence is often linear.[1]



(a) SINR vs. transmit power (b) Achievable rate vs. SINR

Fig. 1: SINR and achievable rate graph

The essence of *greening effect* is that as BSs reduce the transmit powers, the performance degradation does not significantly decrease, yet a considerable overall energy saving is expected due to transmit powers' exerting influence on operational power. Especially, the greening effect becomes conspicuous in the regime of *(i)* interference-limited or *(ii)* high SINR (signal to interference plus noise ratio), where the effect becomes more prominent when both the regimes appear. This is because a considerable reduction in the transmit power leads to just a marginal decrease of SINR at the interference-limited regime, as the thermal noise is dominated by the magnitudes of signal and interference (see Fig.1(a)). Also, according to Shannon capacity formula [5], the achievable rate for users at the high SINR regime logarithmically decreases as SINR decreases (see Fig.1(b)).

Current cellular networks are likely to operate in the interference-limited regime.[2] The regime of high SINR cannot be naturally satisfied, as there always exists a certain portion of low SINR users, e.g., users at the edges of cells, depending on the interference management (IM) scheme. The IM schemes considered in this paper, which dynamically adjust transmit powers, so that even users at the cell edges can increase the achieved SINR, which opens larger room for enjoying more greening effect.

With increasing awareness of the potential harmful impact on the environment by CO_2 emissions and the depletion of

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[1]As an example, the BS power consumption model [4] showed that a macro BS can reduce the total power consumption from 766W to 532W (i.e., 234W saving) just by reducing its transmit power from 20W to 10W.

[2]In a typical cellular network with macro BSs, distances between two neighboring BSs are 500-2000m and the transmit powers of BSs are 10-20W [6]. In such an environment, the magnitude of interferences from other cells can be expected to be often much larger (more than 10 times) than the thermal noise, and accordingly, the network is interference-limited.

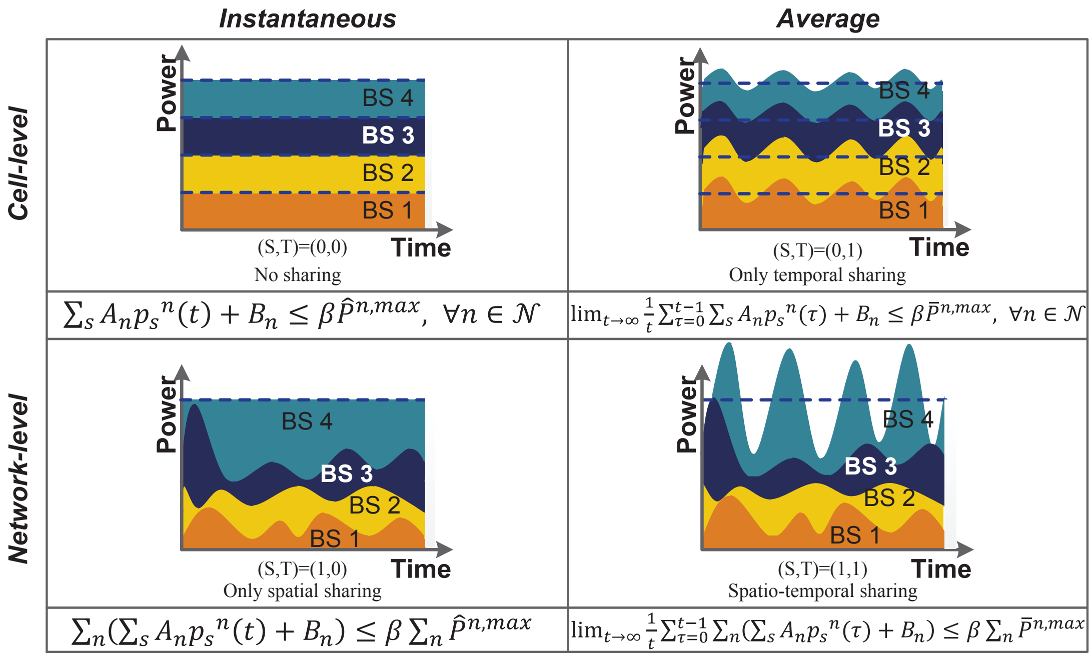


Fig. 2: Four spatio-temporal power sharing policies and constraints.

non-renewable energy sources, there has been a consensus on the need to limit per-nation CO_2 emission, e.g., Kyoto protocol [7]. In the near future, a government is likely to relay such energy-saving pressure to all industries in the country. Pushed by the demand for a greening regulation, wireless service providers (WSPs) may be given the total energy budget, say, per year or month. A brute-force approach is just to decrease the instantaneous power constraint of each individual BS by some portion according to the regulation. However, such an approach seems inefficient because it cannot fully consider the spatial load difference over a space and the temporal channel variation of users. Therefore, one of the most important challenges for WSPs is how to efficiently share the given energy budget.

In this paper, we consider two power sharing policies, *(i) spatial sharing* and *(ii) temporal sharing*, and study their greening effect in the context of IM schemes. In the spatial sharing, we adaptively distribute the power budget across BSs in the network, depending on the variation of arrival traffic. In the temporal sharing, the power budget at each BS is adaptively changed over time, depending on the time-varying channel conditions of users. The time scale of spatial profile is slower than that of temporal profile because the traffic distribution varies depending on the number of users in the system and their locations that is changing relatively slowly compared to the fast channel variation. Fig. 2 depicts four possible combinations of power sharings: *(i)* no sharing, *(ii)* only temporal sharing, *(iii)* only spatial sharing, and *(iv)* both spatio-temporal sharing. We also investigate the impact of four power sharings on the overall operational power in cellular networks based on a realistic BS power consumption model [8].

For radio resource management in downlink cellular networks, throughput or utility maximization objectives subject to given transmit power constraints per each BS [9]–[14] mostly have been considered rather than power minimization objectives subject to the quality of service (QoS) constraints for users [15]. This is because the power consumption on BSs relatively had not been a major concern so far.

Recently, however, there have been efforts to conserve the energy consumption at BSs, which includes [2], [16]–[20] on different control time scales. For example, *(i)* the authors in [16] studied an energy-efficient BS deployment strategy that is an issue of a long time-scale. It is natural that once BSs are deployed, it is hard to change their locations in at least months or even years. *(ii)* In [2], [17], [18], load and location-aware BS switching on/off algorithms were proposed that operate with a fast time-scale (e.g., an order of hours) than the deployment. *(iii)* In [19], the authors considered to incoporate a component-level deceleration with a faster time-scale, called speed-scaling, that is more conservative than turning off BSs, yet can conserve dynamic power effectively. *(iv)* The IM schemes can also bring energy savings, where IM refers to a technology that BSs dynamically control transmit powers on the order of time slots (e.g., an order of milliseconds) to increase the efficiency of spectrum sharing by mitigating inter-cell interference. However, the conventional studies on IM have focused on improving a system performance [10]–[14]. In particular, Venturino *et al.* [10] presented several centralized IM schemes that maximize the sum of long-term utilities of users, and Son *et al.* [13] further proposed a low-complex and fully distributed practical IM algorithm in heterogeneous multi-cell networks.

There was also a greening approach based on IM in the context of wired DSL (Digital Subscriber Line) networks. Tsiaflakis *et al.* [21] proposed a fair-greening framework and showed that when the power of each DSL line is fairly reduced to the half, respectively, the sum of rates can be achieved to more than 85% if appropriate power control algorithms are adopted. It is worthwhile mentioning that these works on wired DSL networks can be interpreted as a special case of wireless multi-cell network, i.e., there is only one user in the cell, so user scheduling is fixed by the user and the wireless channel is fixed for a long time. Accordingly, the greening of wireless multi-cell networks becomes much more challenging than that of wired DSL networks due to the additional user scheduling and stochastic channel variation issues.

The main contributions of this paper are as follows.

1) We exhaustively investigate exploiting the network-wide total BS power budget (including power consumption of power amplifier, cooling system, signal processing, battery power, etc.) in the IM domain under considering greening policy of the government.
2) We suggest four spatial and/or temporal total BS power sharing constraints under the utility maximization framework, and develop joint user scheduling and power allocation per each time slot. To this end, we inherit the ideas of convex approximation in the DSL network [22] at all of policies and greedy primal dual algorithm [23] at the temporal power sharing policies ((S,T)=(0,1) and (S,T)=(1,1)).
3) We observe the several key impacts of IM and spatio-temporal power sharing on the cellular greening: *(i)* the gains both from performance and power saving are obtained by adopting the spatial and/or temporal power sharing policies and the power saving gain of the spatial and/or temporal power sharing is larger than performance gain (i.e., percentage of reduced power consumption is higher than that of increased throughput) due to the greening effect, *(ii)* the tighter greening regulation (i.e., the smaller total power budget) leads to the higher spatio-temporal power sharing gain in terms of performance, *(iii)* spatial power sharing significantly excels temporal one in terms of power saving, and *(iv)* as the cell size becomes smaller, greening effects are greater as well as the greening efficiencies in all policies are larger. These observations suggest that as more greening pressure is given to WSPs, it is important for them to distribute the given power budget spatially to conserve the network-wide BS operational power, especially in a trend which the cell size becomes smaller.

In the rest of this paper, we begin with a description of the system model in Section II. Next, in Section III, we mathematically investigate the impact of different cell sizes on the greening under general power control schemes. In Section IV, we propose greening IM schemes with four different power sharing policies. In Section V, we demonstrate the impact of IM with four power sharing policies on cellular network greening under various topologies and scenarios. Finally, we conclude this paper in Section VI.

II. System Model

A. Network and traffic model

We consider a downlink wireless cellular network with multiple cells. There are N BSs, and K users (or mobile stations), and denote by $\mathcal{N} \doteq \{1, \ldots, N\}$ and $\mathcal{K} \doteq \{1, \ldots, K\}$ the set of BSs and users, respectively. Each of them has one transmit and one receive antenna. Each user can be associated with a single BS. Denote by $\mathcal{K}_n$ the 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 $n \neq m$. All of the adjacent BSs are assumed to communicate with each other via high-speed wired and dedicated backhauls through a centralized BS controller (BSC) for the exchange of control messages.

We assume that each BS has an infinite buffer and always has data for transmission to all associated users. We consider an OFDMA (Orthogonal Frequency Division Multiple Access) system where a subchannel is a group of subcarriers as the basic unit of resource allocation. We further assume that there is no interference across the subchannels. Denote by $\mathcal{S} \doteq \{1, \ldots, S\}$ the set of subchannels, and each BS can use all the subchannels for data transmissions, i.e., universal frequency reuse.

B. Resource and Allocation Model

Consider a time-slotted system indexed by $t = 0, 1, \ldots$. During a slot, the channels are assumed to be invariant. Each BS selects only one user for scheduling and determines the power allocation on each subchannel. Denote by $\boldsymbol{I}_s \doteq [I_s^{k,n} : k \in \mathcal{K}, n \in \mathcal{N}]$ the vector of user scheduling indicators across all users and subchannels, where $I_s^{k,n} = 1$ if BS n schedules user k on subchannel s, and $I_s^{k,n} = 0$ otherwise. Denote by $k(n,s)$ the user scheduled by BS n on subchannel s. In order to reflect an OFDMA constraint that at most only one user can be selected in each subchannel for each BS, we should have:

- *User scheduling constraint:*

$$\sum_{k \in \mathcal{K}_n} I_s^{k,n} \leq 1, \quad \forall n \in \mathcal{N}, s \in \mathcal{S}. \tag{1}$$

Let p_s^n be the transmit power of BS n on subchannel s. The vector containing transmit power of all BSs on subchannel s is $\boldsymbol{p}_s \doteq [p_s^1, \ldots p_s^N]^T$. In parallel, the vector containing transmit powers of all subchannels for BS n is $\boldsymbol{p}^n \doteq [p_1^n, \ldots p_S^n]^T$. There exists a limitation on the maximum level of transmit power at each BS due to a hardware constraint (e.g., power amplifier capability) or regulations from government agencies such as Ofcom in United Kingdom [6], or FCC (Federal Communications Commission) in United States [24] due to harmful effect to human being. In our system model, such limitations are captured by the following constraint:

- *Transmit power constraint:*

$$\sum_{s \in \mathcal{S}} p_s^n(t) \leq \hat{p}^{n,licensed}, \forall n \in \mathcal{N}, \tag{2}$$

where $\hat{p}^{n,licensed}$ is the maximum permitted transmit power level of BS n. We will consider additional power budget constraints later for various power sharing policies in the next section.

C. Link model

We do not consider interference cancelation techniques, and hence users treat the sum of received signal powers from other BSs as a noise in each subchannel. For a power allocation vector $\boldsymbol{p}_s$, the received SINR (signal to interference plus noise ratio) from BS n to user k on subchannel s is denoted by

$$\eta_s^{k,n}(\boldsymbol{p}_s) = \frac{g_s^{k,n} p_s^n}{\sum_{m \neq n} g_s^{k,m} p_s^m + \sigma_s^k}, \tag{3}$$

where $g_s^{k,n}$ and σ_s^k are channel gain from BS n to user k on subchannel s and thermal noise of user k on subchannel s, respectively. The channel gain takes into account fast fading and path loss. Following Shannon's capacity formula [5], the potential data rate of user k associated with BS n on subchannel s is given by

$$r_s^{k,n}(\boldsymbol{p}_s) = \frac{B}{S} \log_2 \left(1 + \eta_s^{k,n}(\boldsymbol{p}_s)\right), \tag{4}$$

where B is the entire system bandwidth. Note that $r_s^{k,n}$ is the meaningful data rate for user k when the user k is selected for service by BS n on subchannel s and actual data rate of the user k becomes 0 when another user is selected. i.e., $r_s^{k,n}(\boldsymbol{p}_s, \boldsymbol{I}_s) = I_s^{k,n} \cdot r_s^{k,n}(\boldsymbol{p}_s)$. For notational simplicity, we omit B/S throughout the paper unless explicitly needed.

III. Greening Effect under Different Cell Size

As the user demand of data traffic grows, the coverage of BSs tends to become smaller to increase the capacity by enjoying a spatial reuse gain. This section examines the greening effect of general power control schemes under different cell size through the mathematical analysis. Suppose that there are multi-cells with radius r. Denote by $p_s^{n,max}$ the transmit power given by any power allocation scheme when the full power budget is given to the BSs. Now, we define following SINR ratio (SR) to analyze the greening effect.

$$\gamma(\theta_n, \phi_n)_s^{k,n} = \frac{g_s^{k,n}(r) p_s^{n,max} \theta_n}{\sigma_s^k + \sum_{m \neq n} g_s^{k,m}(r) p_s^{m,max} \phi_n}, \tag{5}$$

$$SR(\theta_n, \phi_n)_s^{k,n} = \frac{\gamma(\theta_n, \phi_n)}{\gamma(\theta_n = 1, \phi_n = 1)} = \frac{\frac{\theta_n}{\phi_n}(1 + h_s^{k,n}(r))}{\frac{1}{\phi_n} + h_s^{k,n}(r)}, \tag{6}$$

where $h_s^{k,n} = \sum_{m \neq n} g_s^{k,n}(r) p_s^{m,max} / \sigma_s^k$; $0 \leq \theta_n < 1$ and $0 \leq \phi_n < 1$ represent the transmit power ratio of BS n and interference ratio from neighboring BSs to scheduled user associated in BS n, respectively.

If the system uses an equal power allocation (EQ) scheme (i.e., all subchannels equally use the transmit power without any information about wireless environment), θ_n and ϕ_n for each BS are the same. Under the same greening regulation, θ_n and ϕ_n per each BS are determined by each power allocation scheme (e.g., EQ or IM with any power sharing), thus $SR(\theta_n, \phi_n)_s^{k,n}$ are determined by only the noise-normalized interference $h_s^{k,n}(r)$. From the path loss channel model [5], as the cell size becomes smaller, $h_s^{k,n}(r)$ macroscopically becomes higher, consequentially, $SR(\theta_n, \phi_n)_s^{k,n}$ increases due to the fact that $\frac{1}{\phi_n}$ is always bigger than 1. This implies that the cellular system is operated at more interference-limited region. In brief, *the smaller cell size is, the larger greening effect can be expected under any power allocation scheme.*

IV. Greening Interference Management Schemes with Power Sharing Policies

A. Objective and Power Sharing Constraint

Our objective is to develop a slot-by-slot resource allocation, consisting of user scheduling and BS power control, $(\boldsymbol{p}(t), \boldsymbol{I}(t))_{t=0}^{\infty}$, whose long-term user rates are the solution of an optimization problem with the constraints on scheduling and power budget with greening considered. The optimization problem is chosen such that

$$\max \sum_{k \in \mathcal{K}} U_k(x_k), \quad s.t. \quad \boldsymbol{x} \in \boldsymbol{R}(\beta), \tag{7}$$

where $U_k(x_k)$ is the long-term utility function of user k which is continuously differentiable and strictly increasing concave function[3] and $\boldsymbol{R}(\beta)$ is the rate region (a set of all achievable rate vectors by any joint user scheduling and power control). The parameter $\beta \in (0, 1]$, referred to as greening factor, plays an important role in saving power. It controls the amount of power budget reduction ratio based on a greening regulation policy. For instance, when β=1 (no regulation), BSs can use their maximum available powers, however, as β decreases, their power budget is reduced by a factor of β.

Several power sharing policies can be reflected in the above optimization framework as constraints. The power budget constraints of four different power sharing policies are presented in Fig. 2. To refer to each power sharing policy, we henceforth use the notation (S,T) = {(0,0), (0,1), (1,0), (1,1)}. The A_n and B_n are the terms for modeling BS operational power consumption [8], which does and does not depend on the transmit power of BS n, respectively.[4]

The $\hat{P}^{n,max}$ and $\bar{P}^{n,max}$ are instantaneous and average power constraints for BS n, respectively. Note that for a given greening factor β, all power sharing policies guarantee to work under the same long-term system-wide power budget. Each power sharing policy can be classified into *network-level* and *cell-level* power constraints spatially, and *time average* and *instantaneous* power constraints temporally.

B. CASH: Centralized IM Algorithms with Different Power Sharing Policies

Our objective is to develop a slot-by-slot joint user scheduling and BS power control $(\boldsymbol{p}(t), \boldsymbol{I}(t))_{t=0}^{\infty}$ for different power sharing constraints. To this end, we apply a stochastic gradient-based and greedy primal-dual techniques [23], [26] to a long-term utility maximization problem in (7). Then, solving the following optimization problem at each time slot can lead to the asymptotic solution for the original problem in (7). From now on, we suppress the slot index t unless explicitly needed for notational simplicity.

[3] We adopt the general α-proportional fair utility function [25]: $U_k(x_k) = (1-\alpha)^{-1} x_k^{1-\alpha}$ if $\alpha \geq 0$, $\alpha \neq 1$, and $\log x_k$ if $\alpha = 1$.

[4] Typically, A_n and B_n for macro GSM/UMTS BSs depend on the number of sectors, the number of power amplifiers per sector, power amplifier efficiency, cooling loss, battery backup, and so on [8].

(**Slot-by-Slot**) :

$$\max_{\boldsymbol{p},\boldsymbol{I}} \quad \sum_{k\in\mathcal{K}} w_k \sum_{s\in\mathcal{S}} r_s^{k,n}(p_s^n, I_s^n) - \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}} \text{AVE}(p_s^n), \quad (8)$$

$$\text{subject to} \quad \sum_{k\in\mathcal{K}_n} I_s^{k,n} \le 1, \forall n\in\mathcal{N}, \forall s\in\mathcal{S}, \quad (9)$$

$$\sum_{s\in\mathcal{S}} p_s^n(t) \le \hat{p}^{n,licensed}, \forall n\in\mathcal{N}, \quad (10)$$

$$\sum_{s\in\mathcal{S}} A_n p_s^n(t) + B_n \le \beta \hat{P}^{n,max}, \forall n\in\mathcal{N}, \text{if (S,T)} = (0,0), \quad (11)$$

$$\sum_{n\in\mathcal{N}} \Big(\sum_{s\in\mathcal{S}} A_n p_s^n(t) + B_n\Big) \le \beta \sum_{n\in\mathcal{N}} \hat{P}^{n,max}, \text{if (S,T)} = (1,0), \quad (12)$$

where w_k is the derivative of utility $\frac{dU_k(R_k)}{dR_k}|_{R_k=R_k(t)}$ for user k; AVE(p_s^n) is $\gamma_1 p_s^n Q_n^{pc}$ for (S,T) = (0,1), $\gamma_2 p_s^n Q^{pn}$ for (S,T) = (1,1) and 0 otherwise; Here, γ_1 and γ_2 are the step size values which determine tradeoff between the required time for the convergence and the optimality of algorithms. Finally, the virtual queue lengths $Q_n^{pc}(t)$ and $Q^{pn}(t)$ can be updated as follows:

$$Q_n^{pc}(t+1) = \Big[Q_n^{pc}(t) - \frac{\beta \bar{P}^{n,max} - B_n}{A_n} + \sum_{s\in\mathcal{S}} p_s^n\Big]^+, \quad \forall n\in\mathcal{N}, \quad (13)$$

$$Q^{pn}(t+1) = \big[Q^{pn}(t) - (\beta \sum_n \bar{P}^{n,max} - \sum_n B_n) + \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}} A_n p_s^n\big]^+. \quad (14)$$

The key idea is in inheriting spatial power sharing constraints, in conjunction with the scheduling constraint in (9) and the transmit power constraint in (10) [26]. Although the time scale of spatial profile is slower than that of temporal profile, spatial power allocation should be controlled per each time slot due to the scheduling constraint [27]. For temporal constraints, we use the idea of a greedy primal dual algorithm [23] to construct a virtual queue, which is added to the objective function as a penalty function AVE(p_s^n), i.e., if the time-averaged constraint is more violated, then the penalty increases.

We now present CASH (Centralized IM Algorithms with different BS power budget SHaring policies) for user scheduling and power control that can achieve a sub-optimal solution solving (**Slot-by-Slot**) that determines $(\boldsymbol{p}(t), \boldsymbol{I}(t))_{t=0}^{\infty}$. Since the number of available joint power allocation and user scheduling combinations is huge, we take an approach to solve the user scheduling problem for a given power allocation and the power allocation problem for a given user scheduling iteratively until they converge or the maximum number of iteration is reached.[5]

[5]Unfortunately, the convergence of joint user scheduling and power allocation cannot be guaranteed since the problem is a mixed-integer nonlinear programming (MINLP) and has local optima that may not be global optima. However, this technique is as widely accepted in recent literature [10], [13], where the authors proposed similar algorithms with our algorithm.

Lemma IV.1. *For any feasible power allocation $\boldsymbol{p}$, the problem (**Slot-by-Slot**) can be decomposed into $N\times S$ independent intra-cell optimizations for each BS n and subchannel s.*

Proof: For the given power allocation $\boldsymbol{p}$, we can rewrite (8) as follows:

$$\begin{aligned}&\sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{K}_n}\Big[w_k \sum_{s\in\mathcal{S}} I_s^{k,n}\cdot r_s^{k,n}(\boldsymbol{p}_s) - \text{AVE}(p_s^n)\Big] \\ &= \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}}\Big[\sum_{k\in\mathcal{K}_n} w_k\cdot I_s^{k,n}\cdot r_s^{k,n}(p_s) - \text{AVE}(p_s^n)\Big].\end{aligned} \quad (15)$$

As w_k, $r_s^{k,n}(p_s^n)$ and AVE(p_s^n) are given parameters, we only have to consider dependencies among $I_s^{k,n}$. Since the constraint (1) do not play a role across different BSs and subchannels (i.e., independent with the other BSs and subchannels), the original problem is equivalent to independently solving the $N\times S$ subproblems for each BS and subchannel. Hence, the user scheduling at each BS can be represented as follows.

$$I_s^{k,n} = \begin{cases} 1, \text{ if } k = k(n,s) = \text{argmax}_{k\in\mathcal{K}_n} w_k r_s^{k,n}(p_s), \\ 0, \text{ otherwise,}\end{cases} \quad (16)$$

This completes the proof of Lemma IV.1. ■

On the other hand, for a given user scheduling $\boldsymbol{I}(t)$, the problem (**Slot-by-Slot**) can be reduced to the following power allocation problem:

$$\max_{\boldsymbol{p}} \quad \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}}\Big[w_k \log_2\big(1+\eta_s^{k,n}(\boldsymbol{p}_s)\big) - \text{AVE}(p_s^n)\Big], \quad (17)$$

$$\text{subject to} \quad \begin{array}{l}(10) \text{ for all policies,}\\ (11) \text{ for (S,T)} = (0,0),\\ (12) \text{ for (S,T)} = (1,0),\end{array} \quad (18)$$

Unfortunately, even though a user scheduling is given, it is known in [28] that the problem is computationally intractable since the system objective is tightly coupled by the powers of all BSs and nonlinear (neither convex nor concave) function. However, there exist several approximation techniques in literature, see, e.g., [13], [22] and the references therein. With the help of CA-DSB algorithm [22] which is known to be a near-optimal power allocation algorithm in the DSL networks, we apply the similar concave approximation to the non-concave objective function in (17). Please refer to Appendix for more detailed derivation of concave approximation.

For given user scheduling and the concave optimization problem, now we can derive the closed form power allocation by applying Karush-Kuhn-Tucker (KKT) conditions [29].

(User Scheduling and Power Allocation):

$$I_s^{k,n} = \begin{cases} 1, & \text{if } k = k(n,s) = \arg\max_{k\in\mathcal{K}_n} w_k r_s^{k,n}(p_s), \\ 0, & \text{otherwise,}\end{cases} \quad (19)$$

$$p_s^n = \left[\frac{w_{k(n,s)}/\ln 2}{\lambda_n + tax_s^n + V} - \frac{\sum_{m\neq n} g_s^{n,m} p_s^m + \sigma_s^n}{g_s^n}\right]_0^+, \quad (20)$$

$$\begin{aligned}&\text{where } V = \{0,\ \mu,\ \gamma_1 Q_n^{pc},\ \gamma_2 Q^{pn}\} \\ &\text{for (S,T)} = \{(0,0),(1,0),(0,1),(1,1)\},\end{aligned} \quad (21)$$

$$tax_s^n = \sum_{m \neq n} w_m \frac{|g_s^{n,m}|^2 / \ln 2}{\sum_{q \neq n} |g_s^{n,q}|^2 p_s^q + \sigma_s^n} - \sum_{m \neq n} w_m \frac{g_s^{m,n} / \ln 2}{\sum_p g_s^{m,p} p_s^p + \sigma_s^m}, \quad (22)$$

where tax_s^n is the taxation term of BS n on subchannel s taking into account that the power of BS n on subchannel s will give interference to the scheduled users in the neighboring cells. We assume that a BSC obtains all parameters related to the taxation term such as interference and channel gains of each user from each BS. λ_n and μ are non-negative Lagrange multipliers associated with the cell-level and network-level instantaneous BS power constraints, and these two multipliers must be chosen such that the following complementary slackness conditions are satisfied, respectively:

$$\lambda_n \Big(\sum_{s \in \mathcal{S}} A_n p_s^n + B_n - \beta \hat{P}^{n,max} \Big) = 0, \qquad \text{for} \quad \text{(S,T)} = (0,0),$$

$$\lambda_n \Big(\sum_{s \in \mathcal{S}} p_s^n - \hat{p}^{n,licensed} \Big) = 0, \quad \text{for (S,T)} = (0,1) \text{ or (S,T)} = (1,1),$$

$$\lambda_n \Big(\sum_{s \in \mathcal{S}} p_s^n - \hat{p}^{n,licensed} \Big) = 0 \ \text{ and}$$

$$\mu \Big(\sum_{n \in \mathcal{N}} \Big(\sum_{s \in \mathcal{S}} A_n p_s^n + B_n \Big) - \beta \hat{P}^{max} \Big) = 0, \quad \text{for} \quad \text{(S,T)} = (1,0).$$

Given all the other parameters, the closed form equation of p_s^n in (20) is a function of λ_n and μ. Thus, starting from the initial λ_n, μ and the initial power allocation, we can calculate p_s^n for all subchannels and BSs. We iteratively repeat the calculation of p_s^n until the above complementary slackness conditions are satisfied. The proposed CASH algorithm works as follows.

BS Algorithm

1: Estimate channel gains $g_s^{k,n}$ and $g_s^{k,m \neq n}$, $\forall k, s, m$
2: Send $g_s^{k,n}$ and interference, $\forall k, s$ to BSC
3: Receive transmit power $\boldsymbol{p}^n$ and user scheduling $\boldsymbol{I}^n$ from BSC

BSC Algorithm

1: **Initialize** transmit power $\boldsymbol{p}^n$, taxation tax_s^n and receive channel gains from BSs
2: Update virtual queues $Q_n^{pc}(t)$ (for (S,T)=(0,1)), $Q^{pn}(t)$ (for (S,T)=(1,1)) and user weights w_k $\forall k, n, s$ based on previous allocated transmit powers
3: **Repeat** (user scheduling loop):
4: Determine the user scheduling $\boldsymbol{I}^n$ per each cell by (19)
5: Determine the Lagrange multipliers λ_n (for all policies), μ (for (S,T)=(1,0)) in the closed form power allocation (20)
6: Update taxation tax_s^n, $\forall n, s$
7: **Until** user schedulings for all BSs are converged or maximum number of iteration is reached
8: Send the allocated transmit power $\boldsymbol{p}^n$ and user scheduling $\boldsymbol{I}^n$ to each BS

Our CASH algorithm is a centralized algorithm, so the BSC schedules users and allocates powers, then sends its decision to each BS per each time slot. Each BS sends the estimated channel gain and interferences from its associated users to the BSC per each time slot. Given the feedback information from the BSs and an initial power allocation, the BSC first determines users to schedule per each cell by the equation (19). Then, by solving the equation (20), we can obtain power allocation given user scheduling. In the same manner, the BSC iteratively updates powers and scheduled users of each BS until they converge or the maximum number of iteration is reached.

V. Greening Evaluation

A. Simulation Setup

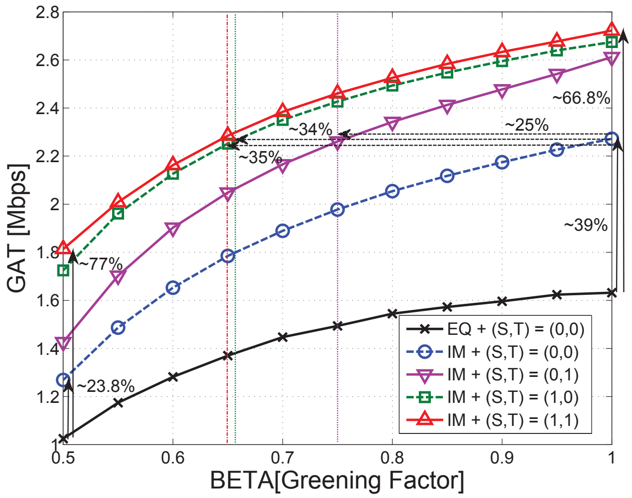
We consider a two-tier macro-cell network composed of hexagonal 19 cells where the distances between BSs are 2km. A wrap around technique is applied in the cells for the same interference environment. We refer to the some parameters and channel model on OFDMA cellular networks from a 802.16m EMD document [30]. The number of subchannels and the regulated (licensed) transmit powers per BS are set to be 8 and 40W, respectively. The total BS power budget for entire system (i.e., 19 BSs) is 14559W.[6] We consider only 7 BSs (i.e., BSs in the 1-tier cells) for the power control. Assume that the other 12 BSs (i.e., BSs in the 2-tier cells) use the fixed transmit power (i.e., 20W per each BS). Maximum instantaneous or average transmit power per each BS under no spatial sharing policies are set to be 20W, respectively. All users who are asymmetrically distributed in 1-7 cells (1-tier) (10 users in 1-3 cell, 20 users in 4-7 cell) are assumed to have a logarithmic utility function, i.e., $\log R_k$. The random shadowing with 8dB deviation and Rayleigh fading and ITU PED-B path loss model ($-16.62 - 37.6 \log_{10} d$[m]) are adopted in modeling the channel. Noise figure of a receive antenna -5dB is added into thermal noise in order to obtain more accurate performance curve with greening factor β. The system bandwidth is 10MHz at 2.3GHz center frequency and the time slot is 1ms.

We verify the rate-power tradeoff of the proposed framework under interference management (IM) with four power sharing policies and conventional equal power allocation (EQ) without any power sharing policies as a baseline. The EQ equally allocates the transmit power for all subchannels with (S,T)=(0,0) and uses proportional fair user scheduling. As a performance metric, the geometric average user throughput (GAT in [Mbps]) is considered since maximizing this metric is equivalent to our system objective. The greening efficiency (GE in [bps/Hz/joule]) is also considered to see how we can energy-efficiently use the total BS power budget in terms of our system objective. Due to limited space, we only provide here our main simulation results about the greening effect of power sharing policies. However, more results are available in our technical report [27], such as the comparison with other IM algorithms, the time scale of spatial profile, the effects of power sharing under the different user density and fairness, etc.

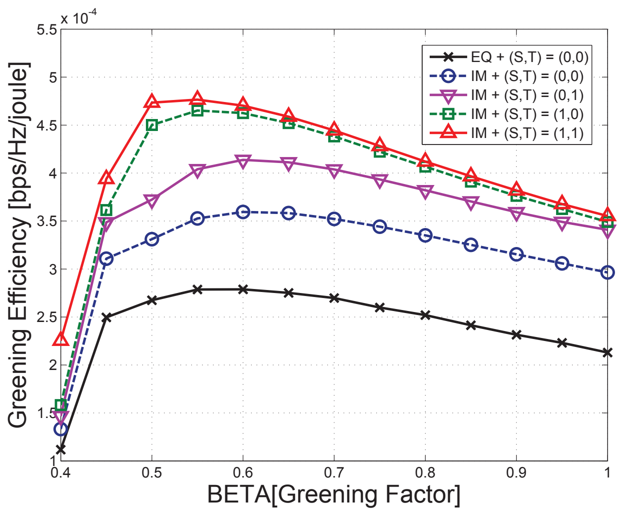
B. Greening Effect of Power Sharing Policies

In Fig. 3, we investigate the GAT and GE performance of different polices by varying the greening factor β. From this

[6]This total power budget is obtained from the real GSM BS power consumption parameters [8] when the average transmit power of BSs is 20W, i.e., A_n = 23.4051, B_n = 298.1815.



(a) GAT-power tradeoff



(b) Greening efficiency

Fig. 3: Greening effects of different power sharing policies (cell radius: 2km)

simulation results, we made four interesting observations.

(Obs.1) The gains both from performance and power saving are obtained by adopting the spatial and/or temporal power sharing policies. Especially, the power saving gain (e.g., at the same GAT of 2.27Mbps, power reduction of IM+(S,T)=(0,0) to IM+(S,T)=(1,1): 35%) excels the performance gain (e.g., at the same greening factor of β=1, GAT increment of IM+(S,T)=(0,0) to IM+(S,T)=(1,1): 20%) since the network is operating in the interference-limited and high SINR regimes in Fig. 1, i.e., enjoying greening effects.

(Obs.2) As greening regulation is tighter (i.e., smaller β) by the government, the spatio-temporal power sharing becomes more important than IM. As the power budget decreases, the spatio-temporal power sharing gain (i.e., increment of EQ+(S,T)=(0,0) to IM+(S,T)=(1,1)) increases (66.8% to 77%) whereas the IM gain (i.e., EQ+(S,T)=(0,0) to IM+(S,T)=(0,0)) decreases (39% to 23.8%). These facts occur mainly due to the following two reasons. If total power budget is gradually reduced, interferences from the other cells also decrease. Hence, the benefit that can be achieved by the inter-cell interference management is marginal. On the other hand, the tighter total power budget we have, the higher spatio-temporal power sharing gain can be expected. This is because the effect of exploiting the different states among cells and time slots would be more important, similar to the philosophy of standard water-filling algorithm.[7]

(Obs.3) Using only spatial power sharing is enough to obtain the most of the power saving gain. We further examine how much gain of each spatial and temporal sharing can bring and which sharing is more important. To this end, we consider the GAT of IM+(S,T)=(0,0) with full power budget (β=1.0) as a baseline performance, and investigate how much power saving can be achieved while guaranteeing the baseline performance through either only temporal IM+(S,T)=(0,1) or spatial sharing IM+(S,T)=(1,0) and both temporal and spatial sharing IM+(S,T)=(1,1). As can be seen in Fig. 3(a), we can reduce 25% or 34% of total power budget by only temporal or spatial sharing, respectively. Interestingly, adopting both temporal and spatial sharing gives us a marginal benefit (from 34% to 35%) compared to the spatial sharing only. These remarks come from the fact that the channel variation due to the spatial profile (i.e., their relative distances to the BS) is greater than that of temporal profile (i.e., random shadowing and fast fading).

(Obs.4) IM and power sharing (especially, spatial sharing) are significantly helpful to increase the greening efficiency. As shown in Fig. 3(b), all schemes have a peak GE point, and greening factors in peak GE of EQ and IM schemes with each power sharing policy are as follows. EQ+(S,T)=(0,0): 0.6, IM+(S,T)=(0,0): 0.6, IM+(S,T)=(0,1): 0.6, IM+(S,T)=(1,0): 0.55, IM+(S,T)=(1,1): 0.55. From these results, it is reasonable to expect that IM schemes with spatial sharing save more power budget with achieving maximal greening efficiency as well as obtain more GE performance than other policies.

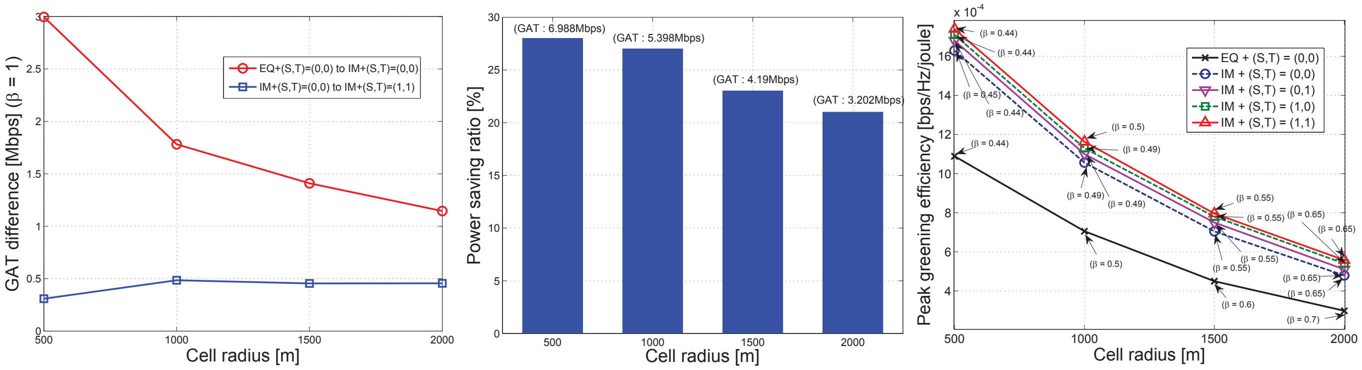
C. Greening Effect on Different Cell Size

In this subsection, we run simulations for IM with power sharing policies on different cell size and validate the accuracy of mathematical analysis, developed in Section III. We simply consider a linear two cell scenario. The number of users are set to be 20 and 10 at each cell, respectively and those who are asymmetrically distributed. All simulation settings are the same as the earlier (e.g., BS power budget, power sharing policy) except for the cell size (500m, 1000m, 1500m, 2000m).

Fig. 4 shows the GAT differences among different power allocation schemes (i.e., EQ+(S,T)=(0,0) to IM+(S,T)=(0,0) and IM+(S,T)=(0,0) to IM+(S,T)=(1,1)) with full power budget (i.e., $\beta = 1$), power saving ratio with fixed GAT performance (i.e., reference performance: IM+(S,T)=(0,0) with $\beta = 1$) and the peak greening efficiencies of different power allocation schemes under the different cell size environment. We could find key observations from these results:

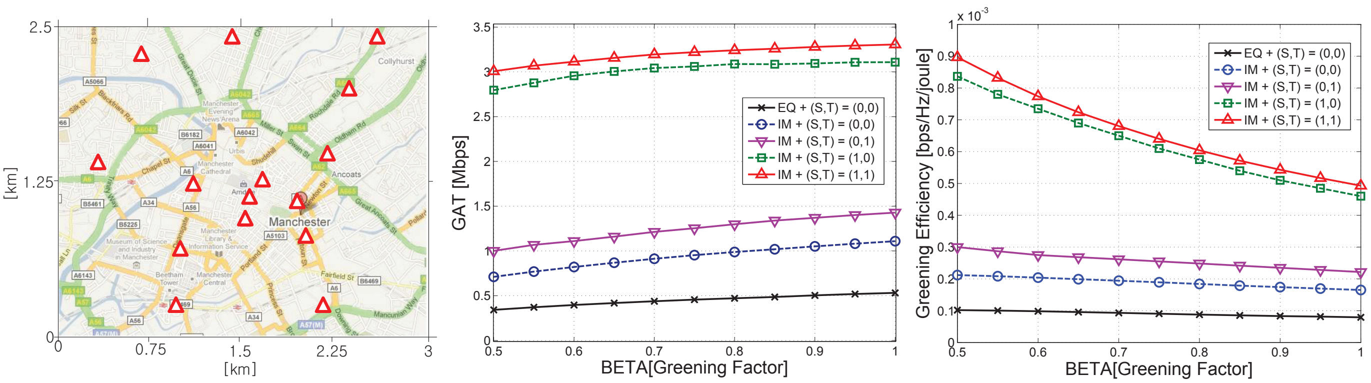
1) As the cell size becomes smaller, greening effects are greater (e.g., lower power budget at peak GE) as well

[7] When the overall power available is less, the effect of exploiting frequency selectivity across subcarriers would be greater.



(a) GAT difference among power allocation schemes (b) Power saving ratio (IM+(S,T)=(0,0) to IM+(S,T)=(1,1)) (c) Peak greening efficiency

Fig. 4: Simulation results on different cell size



(a) Real BS deployment map (b) GAT-power tradeoff (c) Greening efficiency

Fig. 5: Real BS environment simulations

as the greening efficiencies in all policies are larger (see Fig. 4(c)).

2) As the cell size became smaller, IM had a major influence on the improvement of performance gain (see Fig. 4(a)).
3) Even though a contribution of power sharing policy to the performance gain (i.e., improvement of IM+(S,T)=(0,0) to IM+(S,T)=(1,1) in terms of performance) is marginal when the cell size is small (e.g., 500m), power sharing still has a big contribution to the power saving gain (i.e., total power budget reduction under the same performance) (see Fig. 4(b)).

In summary, *IM and power sharing become more important as the cell size decreases in terms of performance, power saving and greening efficiency.*

D. Real UK BS Topology Evaluation

In order to provide more realistic simulation results, we also investigate the greening performance under the part of the macro BS deployment topology in Manchester city, United Kingdom [6][8], as shown in Fig. 5(a). We carry out our simulation under 15 number of BSs (in 3km $\times$ 2.5km) which are owned by T-Mobile Corporation. Maximum licensed transmit power per BS is 63W, and each BS use different transmit power depending on BS location and user density. We assume that the average number of users per cell is almost similar because a small cell covers a region which users are densely distributed and a large cell covers a region which users are sparsely distributed. Under this assumption, we generate users one-by-one in the rectangular area and attach them to the closest BS until each BS will have 10 users.

We investigate the GAT and GE performance at the same manner with the previous simulations (see Fig. 5(b), 5(c)). We could find two interesting remarks in the simulation results: *(i)* a difference of GAT performance between IM with no sharing and spatio-temporal sharing is much higher (e.g., with the full power budget (β=1.0), increment of IM+(S,T)=(0,0) to IM+(S,T)=(1,1): 200%) than the previous regular BS deployment case. *(ii)* The tighter greening regulation is enforced, the greater GE gain is achieved in power sharing policy compared to the previous regular BS deployment case (e.g., with the 50% of full power budget, power sharing gain (i.e., no sharing to spatio-temporal power sharing) ratio of irregular case over regular case is 2.9586, whereas with the full power budget, power sharing gain ratio is 2.4882). These remarks come from the fact that real BSs are irregularly deployed depending on spatial profile (e.g., user densities and distributions), so the

[8]The parameters used in this section V-D for real BS deployment environment can be acquired from Sitefinder [6], where wireless service operator in UK voluntarily provide their BS information, such as BS deployment, transmit power per each BS and maximum licensed transmit power per each BS.

TABLE I: Micro cell effect

	Metrics	Macro cell	Micro cell
EQ +	GAT (Mbps)	0.786	1.15
(S,T)=(0,0)	GE (bps/Hz/joule)	1.03×10^{-4}	1.50×10^{-4}
IM +	GAT (Mbps)	1.15	7.23
(S,T)=(0,0)	GE (bps/Hz/joule)	1.50×10^{-4}	9.44×10^{-4}
IM +	GAT (Mbps)	1.31	7.59
(S,T)=(0,1)	GE (bps/Hz/joule)	1.71×10^{-4}	9.91×10^{-4}
IM +	GAT (Mbps)	1.40	8.23
(S,T)=(1,0)	GE (bps/Hz/joule)	1.83×10^{-4}	10.74×10^{-4}
IM +	GAT (Mbps)	1.47	8.59
(S,T)=(1,1)	GE (bps/Hz/joule)	1.92×10^{-4}	11×10^{-4}

difference of user distribution among cells in real environment is bigger than regular BS deployment case. Therefore, the degree of freedom exploiting power sharing can be larger in real BS deployment case than regular BS deployment case.

E. Micro Cell Effect

In this subsection, in order to clearly see the impact of the micro cell in terms of greening performance on the WSP's perspective, we consider the following two different scenarios: *(i)* macro cell (where the distances between macro BSs are 1km and the operational power parameters with A_n= 23.4051 and B_n= 298.1815 [8]) and *(ii)* micro cell (where the distances between micro BSs are 354m and A_n= 5.238, B_n= 28.86 [8]). The same total BS power per unit area (0.244mW/m^2) and the same number of users per same area (e.g., 64 in a macro cell) are used for a fair comparison. The power consumption models and parameters for macro and micro BS are obtained from [8].

As shown in Table I, *(i) we can see more greening gain (i.e., GAT and GE) in micro-cell scenario than in macro-cell scenario for all schemes, (ii) furthermore, the greening gain growth (i.e., macro-cell to micro-cell performance increase) of the IM with spatio-temporal power sharing is greater than the EQ with no power sharing.* For example, in terms of GAT and GE, there are fourfold (from $1.87 = 1.47/0.786$ to $7.47 = 8.59/1.15$ and from $1.8703 = 1.9184/1.0257$ to $7.3294 = 11/1.5008$) increments, respectively. In conclusion, WSPs would be eager to deploy more micro BSs and use the IM scheme with power sharing than to deploy fewer macro BSs and use the EQ without power sharing at the same coverage in terms of BS operating power consumption.

VI. Concluding Remarks

With increasing energy-saving pressure to WSPs due to harmful impact on the environment by CO_2 emissions, we seriously considered to maximally exploit given power budget of BSs. The main focus of the paper is to analyze the greening effect of interference management (IM) scheme with four combinations of spatial and temporal power budget sharing on multi-cell cellular networks. We formulated optimization theoretic IM frameworks with greening and developed joint power allocation and user scheduling algorithms for different power sharing policies: no sharing, only temporal sharing, only spatial sharing, and both spatial and temporal sharing. Through extensive analytical and simulation studies, we made several important observations, which provide WSPs with guidelines how to energy-efficiently manage their power budget. First, the smart IM with spatial and temporal power sharing has two types of gains: performance and power saving gains. Second, such gains become conspicuous in the near future as the greening regulation would be tighter and/or the cell size of networks would become smaller. Third, the spatial sharing is more important than temporal one in terms of power saving.

Appendix: Concave Approximation

A. Derivation of concave approximation for (17)

$$\max_{\boldsymbol{p}} \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}}\Big[w_k \log_2\big(1+\eta_s^{k,n}(\boldsymbol{p}_s)\big) - \text{AVE}(p_s^n)\Big], \quad (23)$$

$$\begin{aligned} = \max_{\boldsymbol{p}} \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}}\Bigg[& w_k \log_2\Big(\sum_{m\in\mathcal{N}} g_s^{k,m}p_s^m + \sigma_s^k\Big) \\ & - w_k \log_2\Big(\sum_{m\neq n} g_s^{k,m}p_s^m + \sigma_s^k\Big) - \text{AVE}(p_s^n)\Bigg], \end{aligned} \quad (24)$$

$$\begin{aligned} \geq \max_{\boldsymbol{p}} \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}}\Bigg[& w_k \log_2\Big(\sum_{m\in\mathcal{N}} g_s^{k,m}p_s^m + \sigma_s^k\Big) \\ & - w_k \Big(\sum_{m\neq n} a_s^{k,m}p_s^m + c_s^k\Big) - \text{AVE}(p_s^n)\Bigg], \end{aligned} \quad (25)$$

For a given user scheduling $\boldsymbol{I}(t)$, this approximation is similar to the CA-DSB algorithm [22] except for that we should additionally consider time-averaged power constraints. Fortunately, as the virtual queue is fixed during the time slot, so the AVE(p_s^n) is a linear function of p_s^n, and accordingly, it does not affect the concavity of the given function (23). Since the second term of (24) is non-concave (i.e., convex) function while the first and third terms are concave and linear function, respectively, we can approximate the second term of (24) by a lower bound hyperplane in (25). The second term of right part of the equation (25) is the combination of the linear equations, where $a_s^{k,m}$ is the slope of each linear equation, and c_s^k is a constant.

First, given an initial power allocation, we can obtain initial $a_s^{k,m}$ by partially differentiating the second terms of (24) and (25) on p_s^m for all scheduled users in each cell. Then, we insert calculated $a_s^{k,m}$ into the equation (25) and obtain power allocation by applying Karush-Kuhn-Tucker (KKT) conditions [29]. Next, we can determine $a_s^{k,m}$ given power allocation. In the same manner, we can obtain the power allocation until convergence (since the second term of the equation (24) is convex function, it should converge). Additionally, there is no necessity for knowing c_s^k since we do not use c_s^k to calculate the power allocation (20) and (22).

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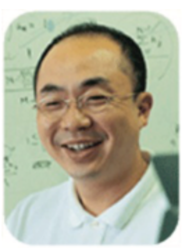

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