Impact of Spatio-Temporal Power Sharing Policies on Cellular Network Greening

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***Abstract*—Greening effect in interference management (IM), which is a technology to enhance spectrum sharing via intelligent BS transmit power control, can be achieved by the fact that even small reduction in BS transmit powers enables considerable saving in overall energy consumption due to their exerting influence on operational powers. In this paper, we study the impact of power sharing policies in IM schemes on cellular network greening, where different spatio-temporal power sharing policies are considered for a fixed system-wide power budget. This study is of great importance in that the pressure on the CO_2 emission limit per nation increases, e.g., by Kyoto protocol, which will ultimately affect the power budget of a wireless service provider. We propose optimization theoretic IM frameworks with greening, from which we first develop four IM schemes with different power sharing policies. Through extensive simulations under various configurations, including a real BS deployment in Manchester city, United Kingdom, we obtain the following interesting observations: (i) tighter greening regulation (i.e., the smaller total power budget) leads to higher spatio-temporal power sharing gain than IM gain, (ii) spatial power sharing significantly excels temporal one, and (iii) more greening gain can be achieved as the cell size becomes smaller.**

I. Introduction

With increasing awareness of the potential harmful impact on the environment by CO_2 emissions and the depletion of non-renewable energy sources, there has been a consensus on the need to limit per-nation CO_2 emission [1]. In the near future, a government is likely to relay such energy-saving pressure to all industries in the country. Information and Communication Technology (ICT) is one of the industries to consume significant amount of energy—a fraction of the world-wide energy consumption ranging from 2% to 10% [2]. In particular, the energy consumed to operate cellular networks reaches 25% of the total ICT energy consumption [3], and the power consumption in base stations (BSs) is one of the dominant components occupying about 60-80% of the total energy 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. As an example, Fehske *et al.* [4] showed that a macro BS can reduce the total power consumption from 766W to 532W (i.e., 234W reduction) just by reducing the transmit power from 20W to 10W. Thus, we are able to enjoy greening effect by employing an appropriate interference management (IM) scheme which can minimize the performance degradation due to the transmit power reduction, especially when the network is interference-limited, e.g., the current cellular network whose cell size is becoming smaller.

Pushed by the demand for greening regulation to limit CO_2 emission, wireless service providers (WSPs) may be given the total energy budget, say, per year or month. A big question to WSPs is how to share the given energy budget temporally and spatially. Their clear objective is to save more energy but degrade performance less. For example, 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 may be inefficient because it cannot fully consider the spatial load difference over space and the temporal channel variation of users.

In this paper, we consider two power sharing policies, (i) *spatial sharing* and (ii) *temporal sharing*, and their impact on the overall 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 topology and user distributions. In the temporal sharing, the power budget at each BS is adaptively changed overtime, depending on the time-varying channel conditions of users, so that the long-term total reduced power budget stays same. Fig. 1 depicts four possible combinations of power sharing. We also investigate their impacts on the overall operational power in cellular networks based on a realistic BS power consumption model [5].

A. Related Work

For radio resource management in downlink cellular networks, rate adaptive objectives [6]–[13] (e.g., throughput or utility maximization) subject to given transmit power constraints per each BS mostly have been considered rather than margin adaptive objectives [14] (e.g., power minimization) subject to quality of service (QoS) constraints for users. This is because the power consumption on BSs relatively had not been a major concern so far.

Related work on BS energy saving includes [2], [15], [16] which consider different issues with different time scales. For

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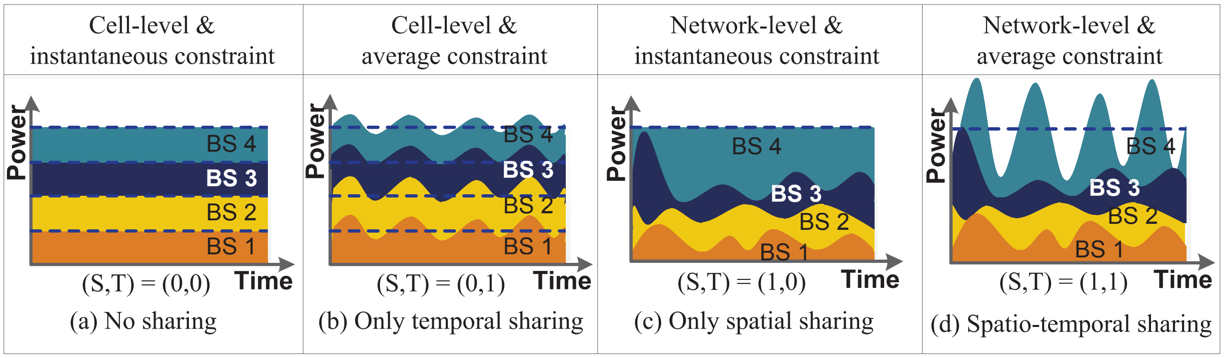

(a) No sharing (b) Only temporal sharing (c) Only spatial sharing (d) Spatio-temporal sharing

Fig. 1: Four spatio-temporal power sharing policies.

example, the authors in [15] studied an energy-aware BS deployment strategy that is an issue of a long time-scale. It is natural that once BSs are deployed, it hard to change their locations in at least months or even years. In [2], [16], the authors proposed load and location-aware BS switching on/off algorithms that operate with a faster time-scale (e.g., an order of hours) than the deployment. The IM schemes can also bring energy saving, where IM refers to the technology that BSs dynamically control powers in the order of time slots to increase the efficiency of spectrum sharing by mitigating inter-cell interference. However, the conventional studies on IM have focused on improving system performance by mitigating inter-cell interference [8]–[13]. In particular, Venturino *et al.* [8] presented several centralized IM schemes that maximize the sum of long-term utilities of users, and Son *et al.* [12] further proposed 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.* [17], [18] proposed fair-greening frameworks and showed that when the power of each DSL line is fairly reduced to the half, respectively, the sum of rate can be achieved to more than 85% if appropriate power control algorithms are adopted. Their papers are based on [19], which deals with power control algorithm to mitigate crosstalk of DSL network. This can be regarded 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 wireless channel is fixed for a long time. Accordingly, we need more complex consideration in greening of wireless multi-cell cellular networks than wired DSL networks due to the additional user scheduling and stochastic channel variation issues.

B. Contributions and Organization

The main contributions of this paper are as follows

1) We develop an optimization based greening IM framework with four BS power sharing policies. Also, we develop four different IM algorithms with joint user scheduling and power allocation per each time slot, each of which is with one sharing policy. Since we consider long-term BS power budget, we introduce a virtual queue which reflects average power constraints.
2) Throughout extensive simulations based on a real BS deployment, we obtain many interesting observations: *(i)* power saving gain outshines performance gain due to the fact that the network is interference-limited. *(ii)* Tighter greening regulation (i.e., the smaller total power budget) leads to higher spatio-temporal power sharing gain, *(iii)* spatial power sharing significantly excels temporal one, and *(iv)* more greening and performance gain are achieved as the cell size becomes smaller, e.g., femto/pico cells. These observations suggest that as more greening pressure is given to WSPs, it is important to distribute the given power budget spatially, and smart IM becomes more important as the cell size becomes smaller.

The remainder of this paper is organized as follows. In Section II, we present our system model. In Section III, we propose greening IM schemes with four different power sharing policies. In Section IV, we demonstrate the impact of four power sharing policies on cellular network greening under various topologies and scenarios. Finally, we conclude the paper in Section V.

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 (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. BS (or user) 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 dedicate backhauls directly or through a centralized BS controller (BSC).

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. Assume 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 the constraint that at most only one user can be selected in each subchannel for each BS, we should have:

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

Let p_s^n be the transmit power of BS n on subchannel s, and let $\boldsymbol{p}_s \doteq [p_s^1, \ldots p_s^N]^T$, and $\boldsymbol{p}^n \doteq [p_1^n, \ldots p_S^n]^T$. There exists a maximum level of transmit power at each BS due to a hardware constraint (e.g., power amplifier capability) or regulations from government agencies due to harmful effect to humans [20], [21]. We will consider additional power 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

$$\eta_s^{k,n}(\boldsymbol{p}_s) = \frac{g_s^{k,n} p_s^n}{\sum_{m \neq n} g_s^{k,m} p_s^m + \sigma_s^k}, \tag{2}$$

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 random shadowing, Rayleigh fading, and path loss. Following Shannon's capacity formula [22], the potential data rate of user k associated with BS n on subchannel s is given by

$$r_s^{k,n}(\boldsymbol{p}_s) = \frac{B}{S} \log_2 \left(1 + \eta_s^{k,n}(\boldsymbol{p}_s)\right), \tag{3}$$

where B is the 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 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 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

$$\max \sum_{k \in \mathcal{K}} U_k(x_k), \quad s.t. \quad \boldsymbol{x} \in \boldsymbol{R}(\beta), \tag{4}$$

where $U_k(x_k)$ is the long-term utility function of user k which is continuously differentiable and strictly increasing concave function 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 β is due to the power budget constraint which we parameterize by the greening factor β.

A power sharing policy is reflected in the above optimization framework as a constraint. The power budget constraints of four different power sharing policies are presented in Table I. 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 for modeling BS operational power consumption [5], which may or may not depend on the transmit power of BS n, respectively. The $\hat{P}^{n,max}$ and $\bar{P}^{n,max}$ are instantaneous and average power constraints for BS n, respectively. Greening factor $\beta \in (0, 1]$ controls the amount of power budget reduction, e.g., given by a greening regulation policy. Note that for a given β, all power sharing policies guarantee to work under the same long-term system-wide power budget. Irrespective of sharing policies, the basic transmit power constraint regulated by the hardware as well as the government agencies is imposed by $\sum_s p_s^n(t) \leq \hat{p}^{n,licensed}$. 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. Greening IM Algorithms

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], [24] to long-term utility maximization problem in (4). Then, solving the following optimization problem at each time slot can lead to the asymptotically optimal solution. From now on, we suppress the slot index t unless explicitly needed for notational simplicity.

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

$$\max_{\boldsymbol{p}, \boldsymbol{I}} \quad \sum_{k \in \mathcal{K}} w_k \sum_{s \in \mathcal{S}} r_s^{k,n}(p_s^n, I_s^n) - \sum_{n \in \mathcal{N}} \sum_{s \in \mathcal{S}} \text{AVE}(p_s^n), \tag{5}$$

$$\text{subject to} \quad \sum_{k \in \mathcal{K}_n} I_s^{k,n} \leq 1, \forall n \in \mathcal{N}, \forall s \in \mathcal{S}, \tag{6}$$

$$\sum_{s \in \mathcal{S}} p_s^n(t) \leq \hat{p}^{n,licensed}, \forall n \in \mathcal{N}, \tag{7}$$

$$\sum_{s \in \mathcal{S}} A_n p_s^n(t) + B_n \leq \beta \hat{P}^{n,max}, \forall n \in \mathcal{N}, \text{if (S,T) = (0,0)}, \tag{8}$$

$$\sum_{n \in \mathcal{N}} \Big(\sum_{s \in \mathcal{S}} A_n p_s^n(t) + B_n \Big) \leq \beta \sum_{n \in \mathcal{N}} \hat{P}^{n,max}, \text{if (S,T) = (1,0)}, \tag{9}$$

where w_k is the derivative of utility $\frac{dU_k(R_k)}{dR_k}|_{R_k = R_k(t)}$ for user k; $\text{AVE}(p_s^n)$ is $\gamma_1 p_s^n Q_n^{pc}$ for (S,T) = (0,1), $\gamma_2 p_s^n Q^{pn}$ for

TABLE I: Constraints for Power Sharing Policies

Sharing policy	Notation	Constraints
No sharing	(S,T) = (0,0)	$\sum_s A_n p_s^n(t) + B_n \leq \beta \hat{P}^{n,max}, \quad \forall n \in \mathcal{N}$
Only temporal sharing	(S,T) = (0,1)	$\lim_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \sum_s A_n p_s^n(\tau) + B_n \leq \beta \bar{P}^{n,max}, \quad \forall n \in \mathcal{N}$
Only spatial sharing	(S,T) = (1,0)	$\sum_n \Big(\sum_s A_n p_s^n(t) + B_n \Big) \leq \beta \sum_n \hat{P}^{n,max}$
Spatio-temporal sharing	(S,T) = (1,1)	$\lim_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \sum_n \Big(\sum_s A_n p_s^n(\tau) + B_n \Big) \leq \beta \sum_n \bar{P}^{n,max}$

(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 convergence and the optimality of algorithms. Finally, the virtual queue lengths $Q_n^{pc}(t)$ and $Q^{pn}(t)$ can be updated as follows:

$$Q_n^{pc}(t+1) = \Big[Q_n^{pc}(t) - \frac{\beta \bar{P}^{n,max} - B_n}{A_n} + \sum_{s\in\mathcal{S}} p_s^n \Big]^+, \quad \forall n \in \mathcal{N}, \tag{10}$$

$$Q^{pn}(t+1) = \big[Q^{pn}(t) - (\beta \sum_n \bar{P}^{n,max} - \sum_n B_n) + \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}} A_n p_s^n \big]^+. \tag{11}$$

The key idea is that we inherit spatial power sharing constraint, in conjunction with the scheduling constraint in (6) and the transmit power constraint in (7) [23]. For temporal constraint, we use the idea of a greedy primal dual algorithm [24] and introduce 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 an algorithm of user scheduling and power control 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 can solve user scheduling for a given power allocation and power allocation for a given user scheduling iteratively until it converges. Unfortunately, even though user scheduling is given, it is known in [25] 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. There exist several approximation techniques in literature, see, e.q., [19] and the references therein.

For a given power allocation, the slot-by-slot framework can be decomposed into user scheduling at each cell (19). Users are selected depending on the user weight and the potential rate for each time-slot as following lemma.

Lemma 3.1: If there exists any given feasible power allocation $\boldsymbol{p}$ for the problem (**Slot-by-Slot**), then it can be reduced to $N \times S$ independent intra-cell optimizations for each BS n and subchannel s.

Proof: For the given power allocation $\boldsymbol{p}$, we can rewrite (5) as follows:

$$\begin{aligned} &\sum_{n\in\mathcal{N}} \sum_{k\in\mathcal{K}_n} \Big[w_k \sum_{s\in\mathcal{S}} I_s^{k,n} \cdot r_s^{k,n}(\boldsymbol{p}_s) - \text{AVE}(p_s^n) \Big] \\ &= \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}} \Big[\sum_{k\in\mathcal{K}_n} w_k \cdot I_s^{k,n} \cdot r_s^{k,n}(p_s) - \text{AVE}(p_s^n) \Big]. \end{aligned} \tag{12}$$

As w_k, $r_s^{k,n}(\boldsymbol{p}_s)$ 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, the original problem is equivalent to independently solving the $N \times S$ subproblems for each BS and subchannel. This completes the proof. ■

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

$$\max_{\boldsymbol{p}} \quad \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}} \Big[w_k \log_2\big(1+\eta_s^{k,n}(\boldsymbol{p}_s)\big) - \text{AVE}(p_s^n) \Big], \tag{13}$$

$$\text{subject to} \quad \begin{cases} (7) \text{ for all policies,} \\ (8) \text{ for (S,T)} = (0,0), \\ (9) \text{ for (S,T)} = (1,0), \end{cases} \tag{14}$$

With the help of the CA-DSB algorithm [19] which is known to be near optimal power allocation algorithm in the DSL networks, we apply the same concave approximation to the non-concave objective function in (13) as follows.

$$\max_{\boldsymbol{p}} \quad \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}} \Big[w_k \log_2\big(1+\eta_s^{k,n}(\boldsymbol{p}_s)\big) - \text{AVE}(p_s^n) \Big], \tag{15}$$

$$\begin{aligned} = \max_{\boldsymbol{p}} \quad &\sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}} \Big[w_k \log_2 \Big(\sum_{m\in\mathcal{N}} g_s^{k,m} p_s^m + \sigma_s^k \Big) \\ &- w_k \log_2 \Big(\textstyle\sum_{m\neq n} g_s^{k,m} p_s^m + \sigma_s^k \Big) - \text{AVE}(p_s^n) \Big], \end{aligned} \tag{16}$$

$$\begin{aligned} \geq \max_{\boldsymbol{p}} \quad &\sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}} \Big[w_k \log_2 \Big(\sum_{m\in\mathcal{N}} g_s^{k,m} p_s^m + \sigma_s^k \Big) \\ &- w_k \Big(\textstyle\sum_{m\neq n} a_s^{k,m} p_s^m + c_s^k \Big) - \text{AVE}(p_s^n) \Big], \end{aligned} \tag{17}$$

For a given user scheduling $\boldsymbol{I}(t)$, this approximation is similar to CA-DSB algorithm except for that we also should consider time average power constraints. Fortunately, virtual queue is fixed during the time slot, so AVE(p_s^n) is linear function of p_n^s, which has not effect on the concavity of the given function (15). Since the second term of the equation (16) is non-concave (convex) while the first and third terms are concave and linear function, we can approximate the second term of the equation (16) by a lower bound hyperplane as the equation (17). The approximation parameters $a_s^{k,m}$ $(\forall m)$ are obtained by solving a linear system of N equations on N unknowns. We determine p_s^n $(\forall n, \forall s)$ by following power allocation procedures under given approximation parameters $a_s^{k,m}$ $(\forall m)$ and determine $a_s^{k,m}$ $(\forall m)$ under given power allocation iteratively until the power allocations are converged. By applying this lower bound approximation, the objective in (15) can be transformed into the following concave function:

$$\sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}}\Bigg[w_k\log_2\Bigg(\sum_{m\in\mathcal{N}} g_s^{k,m}p_s^m+\sigma_s k\Bigg) - w_k\Bigg(\sum_{m\neq n} a_s^{k,m}p_s^m + c_s^k\Bigg) - \text{AVE}(p_s^n)\Bigg]. \tag{18}$$

For given user scheduling and concave optimization problem, now we can derive the closed form power allocation by applying Karush-Khun-Tucker (KKT) conditions [26].

(User Scheduling and Power Allocation):

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

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

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

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

where tax_s^n is a taxation term of BS n on subchannel s reflecting that the power of BS n on subchannel s will give interferences to the scheduled users in the neighboring cells.

We assume that all parameters related to taxation term such as interference, allocated power of the other BSs, channel gains and weights of users in the other cells are obtained by a centralized BSC. 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:

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

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

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

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

TABLE II: Algorithm Description for (S,T)={(0,0),(0,1),(1,1)}

BS Algorithm

Virtual queues update & exchange among BSs through BSC
Power initialization
repeat (user scheduling loop):
  User scheduling (given power allocation)
  repeat (power allocation loop):
    λ_n^{min}, λ_n^{max} decision
    Taxation update from BSC
    while
      λ_n = (λ_n^{min}+λ_n^{max})/2
      update p_s^n, $\forall s$ from (21)
      if $\sum_s A_n p_s^n + B_n > \beta\hat{P}^{n,max}$
       for (S,T)={(0,0),(0,1)}
      or $\sum_s p_s^n > \hat{p}^{n,licensed}$ for (S,T) = (1,1)
      then, $\lambda_n^{min} \leftarrow \lambda_n$
      else then, $\lambda_n^{max} \leftarrow \lambda_n$
    until $\boldsymbol{p}^n$ converges or max # of iterations is reached
    Measure $int_s^n = \sum_{p\neq n} g_s^{n,p}p_s^p + \sigma_s^n, \forall s$
    Transmit $int_s^n, p_s^n, g_s^n, w_n$ to BSC, $\forall s$
until $\boldsymbol{I}^n$ converges or max # of iterations is reached

BSC Algorithm

Share the information of the virtual queues among BSs.
repeat :
  Receive messages $int_s^n, p_s^n, g_s^n, w_n$ from BS n, $\forall n$
  Compute taxation and send to each BS n, $\forall n$
until $\boldsymbol{I}^n$ of all BSs converge or max # of iterations is reached

Given all other parameters, the closed form equation of p_s^n in (20) is a function of λ_n and μ. Starting from the initial power allocation, λ_n and μ, we can calculate p_s^n for all subchannels and BSs. We iteratively repeat the calculation of p_s^n until above complementary slackness conditions are satisfied. BS and BSC algorithms are given by Table II for (S,T) = {(0,0), (0,1), (1,1)}, and Table III for (S,T) = (1,0).

C. Cost of Power Sharing Policies

Now let us discuss the implementation cost of the power sharing policies ((S,T) = (1,0) , (0,1) , (1,1)) compared to no sharing policy ((S,T) = (0,0)), in terms of *(i)* algorithmic and *(ii)* transmit power usage perspectives.

From the algorithmic point of view, in order to calculate power allocation (20) without any power sharing, we need to exchange allocated power, channel gains and weights from the scheduled user in the cell and other cells with BSC. Even though we have to manage virtual queues or additional Lagrange multiplier and complementary slackness condition per each time-slot under temporal or spatial power sharing

TABLE III: Algorithm Description for (S,T) = (1,0)

BS Algorithm

repeat :

  Receive p_s^n, $I_s^{k,n}$ from BSC $\forall s$

  Calculate int_s^n, g_s^n, w_n $\forall s$ and send to BSC

until $\boldsymbol{I}$ converges or max # of iterations is reached

BSC Algorithm

Receive initial values int_s^n, p_s^n, g_s^n, w_n, virtual queues from each BS n, $\forall s$, $\forall n$

Power initialization

repeat (user scheduling loop):

  User scheduling (given power allocation)

  repeat (power allocation loop):

  μ^{min}, μ^{max} decision

  while

    μ = $(\mu^{min}$+$\mu^{max})$/2, for each BS, λ_n^{min}, λ_n^{max} decision

    while

      λ_n = $(\lambda_n^{min}$+$\lambda_n^{max})$/2

      Taxation update from (22), update p_s^n from (20), $\forall s$

      send $\boldsymbol{p}^n$, $\boldsymbol{I}^n$ to each BS n, $\forall n$, receive int_s^n, g_s^n, w_n from each BS n, $\forall s$, $\forall n$

      if $\sum_s p_s^n > \hat{p}^{n,licensed}$ then, $\lambda_n^{min} \leftarrow \lambda_n$

      else then, $\lambda_n^{max} \leftarrow \lambda_n$

    until p_n converges or max # of iterations is reached

    if $\sum_n(\sum_s A_n p_s^n + B_n) > \beta \sum_n P^{n,max}$

     then, $\mu^{min} \leftarrow \mu$,

     else then, $\mu^{max} \leftarrow \mu$

  until $\boldsymbol{p}$ converges or max # of iterations is reached

until $\boldsymbol{I}$ converges or max # of iterations is reached

policies, we do not need to exchange any more information with BSC. Therefore, only a little computational overhead is needed to temporally or spatially share the given power budget.

From the transmit power usage point of view, there are physical hardware constraints (e.g., power amplifier capability in BSs) and regulations by organizations such as Ofcom in the United Kingdom [20] or FCC (Federal Communications Commission) in the United States [21]. We obey these constraints by the constraint term (7), so we do not need any additional cost (e.g., power amplifier upgrade or penalty cost of over usage of transmit power from regulation authorities) in the transmit power usage perspective.

IV. 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. Wrap around techniques are applied in the cells for the same interference environment. We refer to the some parameters and channel model on OFDMA cellular networks from 802.16m standard document [27]. The number of subchannels and the regulated transmit powers per BS are set at 8 and 40W, respectively. Total BS power budget (for 19 BSs) is 14559W[1]. All users are assumed to have a logarithmic utility function, i.e., $\log R_k$. The random shadowing with 8dB deviation and Reyleigh fading and ITU PED-B path loss model ($-16.62 - 37.6 \log_{10} d$[m]) are adopted in communication channel. Noise figure of receiver antenna is added into thermal noise to obtain more accurate performance curve with greening factor β. The simulation parameters are summarized in Table IV.

TABLE IV: Simulation Parameters

· Number of subchannels : 8
· Max tx power per each BS for (S,T) = {(0,0), (0,1)}: 20W
· Max licensed (regulated) tx power per BS : 40W
· Total system-wide BS power budget : 14559W
· Number of BSs : 19
· Number of users per each cell: 10
· Radius of BS (Macro cell) : 2km
· α (fairness criterion) : 1.0 (proportional fair)
· Bandwidth : 10MHz per each channel
· Length of time slot : 1ms
· Center frequency : 2.3GHz
· Shadowing deviation : 8dB
· Thermal noise : 174dBm
· Noise figure of receiver antenna : 5dB

We verify the rate-power tradeoff of the proposed frameworks under interference management (IM) with four power sharing policies and conventional equal power allocation (EQ) without any spatio-temporal sharing 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 throughput.

B. Greening Effect of Power Sharing Policies

In Fig. 2, we first investigate the GAT performance of different polices by varying the greening factor β. From this result of greening effect, we made three interesting observations.

(Obs.1) More power saving gain is achieved compared to performance gain when we adopt spatio-temporal power sharing policy. With the full power budget (β =1.0), power saving gain of spatio-temporal power sharing policy (i.e., power saving at the same performance with no power sharing (IM with (S,T)=(0,0)): 35%) is higher than performance gain (i.e., increment of IM with (S,T)=(0,0) to (S,T)=(1,1): 20%) due to insensitivity of performance curve by the fact that the network is interference-limited.

[1]This total power budget is obtained from the real GSM BS power consumption parameters [5] when the average transmit power of BSs is 20W.

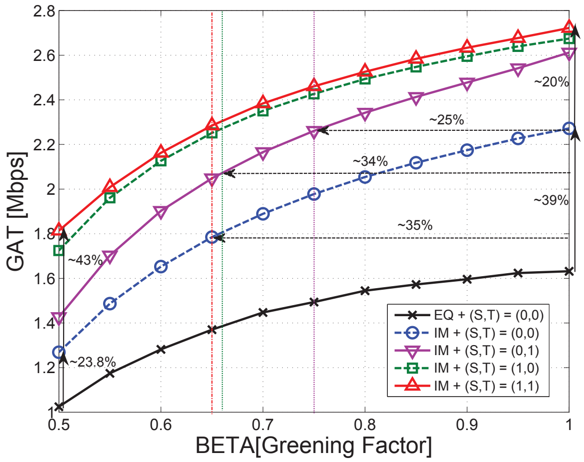

Fig. 2: GAT-power tradeoff.

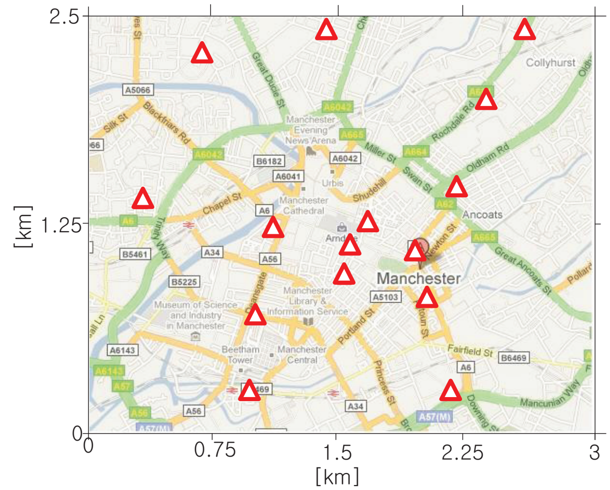

Fig. 3: Real BS deployment map.

(Obs.2) The tighter greening regulation (i.e., smaller β) by the government is, the higher spatio-temporal power sharing gain is expected. With the full power budget (β=1.0), spatio-temporal power sharing gain (i.e., increment of IM with (S,T)=(0,0) to (S,T)=(1,1): 20%) is smaller than interference management gain (i.e., increment of EQ to IM with (S,T)=(0,0): 39%). However, as the power budget decreases, the sharing gain is larger than interference management gain. For example, at the half power budget (β=0.5), the sharing gain (23.8%) is almost as two times as the interference management gain (43%).

(Obs.3) Using only spatial power sharing is enough to obtain the most of the performance gain. We further examine how much gain each spatial and temporal sharing can bring and which sharing is more important. To this end, we consider the GAT of (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 (S,T)=(0,1) or spatial sharing (S,T)=(1,0) and both temporal and spatial sharing (S,T)=(1,1). As can be seen in Fig. 2, 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.

C. 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 [20][2], as shown in Fig. 3. 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 whereas each BS use different transmit power depends on BS location and user density. Assuming the deployment of BSs in Manchester city have been done according to the average user density, we consider all of BSs in the network has same number of associated users.

[2]Parameters of BS deployment, transmit power per each BS and maximum licensed transmit power per each BS which are voluntarily given by wireless service operator of UK can be acquired from this website.

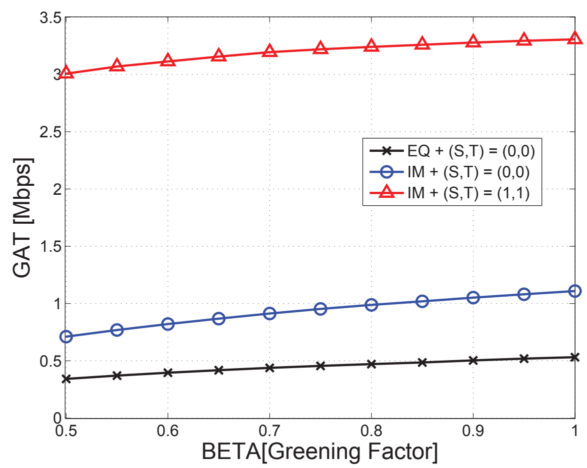

Fig. 4: GAT-power tradeoff in real BS topology.

In Fig. 4, we investigate the GAT performance in the same manner of previous simulation. The interesting remark comes from performance gap between IM with no sharing and spatio-temporal sharing(e.g., with the full power budget (β=1.0), increment of IM with (S,T)=(0,0) to (S,T)=(1,1): 200%) which is much higher than the previous regular BS topology scenario. This is because real BSs are irregularly deployed depending on several environment (e.g., user density), so user distribution among cells in real environment is more asymmetric than regular BS deployment case. Therefore, the degree of freedom exploiting power sharing can be greater in real BS deployment case than regular BS deployment case.

TABLE V: Small cell effect

	Metrics	Large cell (Macro BS)	Small cell (Micro BS)
EQ + (S,T)=(0,0)	GAT	0.786	1.15
	GE	0.0042	0.0082
IM + (S,T)=(1,1)	GAT	1.47	8.59
	GE	0.0063	0.0369

D. Small Cell Effect

Small cell is an inevitable trend in the next generation cellular network to maximally exploit the spectral resource. In order to clearly see the impact of the cell size on the greening and performance, we consider the following two different scenarios: *(i)* large cell (where the distances between macro BSs are 1km) and *(ii)* small cell (where the distances between micro BSs are 354m). The same total BS power per unit area (0.244mW/m^2) and the same number of users per same area are used for a fair comparison. The power consumption models and parameters for macro and micro BS are obtained from [5]. As shown in Table V, *we can see more greening gain in small-cell scenario than that in large-cell scenario.* 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 threefold (from $1.5 = 0.0063/0.0042$ to $4.5 = 0.0369/0.0082$) increments, respectively.

V. CONCLUSION

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. This paper focused on analyzing the impact of four combinations of spatial and temporal power budget sharing on cellular networks from a greening perspective. We formulated optimization theoretic IM frameworks with greening and developed joint power allocation and user scheduling algorithms for different power sharing policies. Through extensive simulations, we investigated that two types of gain of the IM framework with four power sharing policies: performance and power saving gains. The simulation results reveal that smart IM and efficient power sharing policies will be more crucial in the near future, in which the greening regulation would be tighter and the cell size of networks would become smaller.

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