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

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Abstract

In this paper, we analyze short-time scale BS (Base Station) power saving controlling transmit power and scheduling users of each BS on multi-cell multi-carrier cellular networks. Although the transmit power of a typical macro BS is lower (10W-20W) than total BS power consumption (500W-2000W), the transmit power also exerts influence linearly on the power consumption of power amplifiers and cooling systems and battery backup and power supply loss in the BS. Even with a transmit power reduction, users can expect high performance when they are in the interference-limited region and appropriate power control and user scheduling algorithms are adopted. Through simple simulations under EQ (equal power allocation) and IM (interference management) cases, we verify that more than 76% throughput can be obtained for edge and center users only with a 1/5 of transmit power. Furthermore, we propose four BS power sharing policies which are novel greening policies exploiting temporal and spatial degree of freedom with fixed fairness criterion (proportional fair) and present power allocation and user scheduling algorithms to meet asymptotically near optimal solutions of given framework. 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. Through extensive simulation, we verify that the impact of proposed power sharing policies on BS power saving. Besides, we show more outstanding greening performance of IM and spatio-temporal power sharing than IM and no spatio-temporal power sharing through the simulations under the part of the Manchester city, UK (United Kingdom) irregular BS deployment and power consumption scenarios. Furthermore, we verify greening performance of our frameworks on the small cell (such as micro and femto cell) which is an inevitable trend in the next generation cellular network to maximally exploit the spectral resources. A promising conclusion in drawn that higher GAT and greening efficiency are achieved with smaller cell sizes when applying IM and spatio-temporal power sharing with network-level average power constraint than EQ with no

spatio-temporal power sharing.

Keywords: Base station, transmit power, greening effect, spatio-temporal power sharing policies, small cell, greening efficiency

I. INTRODUCTION

A. Overview and Motivation

Recently, increasing awareness of the potential harmful effects to the environment caused by greenhouse gas emissions and the depletion of non-renewable energy sources have led to a growing consensus on the need to develop more energy-efficient telecommunication systems. Out of the total industries, Information and Communication Technology (ICT) is known for the most energy consuming industry and it is responsible for a fraction of the world energy consumption ranging between 2% and 10% [1]. In particular, energy consumption of cellular network represents the 25% of total ICT energy consumption [2]. Moreover, total base stations (BSs) contribute between 60% to 80% of energy consumption of the whole cellular network [1]. Although a typical BS consumes power just between 500W to 2000W [3], there are many more number of BSs than core network which consume 10kW per each equipment in the whole cellular network. Moreover, the total mobile terminals in cellular network consume only 1/10 of the total BSs power consumption.

With such awareness about importance of BS greening, there has been an increasing interest and several efforts to reduce BS power consumption so far. There are three temporal approaches to reduce BS energy consumption. First approach is power efficient BS deployment with long-time scale (semi-permanent) [4], the second approach is BS on/off scheme [1], [5], [6] or joint BS operation and user association [7] with a mid-time scale (several days or hours), the last approach is situation (interference or load) aware BS transmit power control with a short-time scale (few msec or sec). We deal with last approach in this paper.

In order to deal with short-term BS power control, we should consider power consumption model of BS. The BS power consumption can be modeled with transmit output power varying with short-time scale and other terms which are constant with short-time scale as follows [8].

$$P_{Macro} = N_{sector} \cdot N_{PApSec} \cdot \left[\frac{\bar{p}_{tx}}{\mu_{PA}} + P_{SP} \right] \cdot (1 + C_c) \cdot (1 + C_{PSBB}) \tag{1}$$

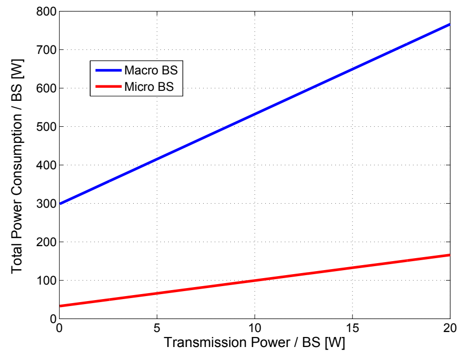


Fig. 1. Total power consumption vs. transmit power

$$P_{Micro,static} = \left[\frac{\bar{p}_{tx}}{\mu_{PA}} C_{TX,static} + P_{SP,static}\right] \cdot (1 + C_{PS}) \tag{2}$$

$$P_{Micro,dynamic} = \left[\frac{\bar{p}_{tx}}{\mu_{PA}} (1 - C_{TX,static}) \cdot C_{TX,NL} + P_{SP,NL}\right] \cdot N_L \cdot (1 + C_{PS}) \tag{3}$$

where P_{Macro}, $P_{Micro,static}$, $P_{Micro,dynamic}$ and $\bar{p}_{tx}$ are total power consumption of macro, micro BSs (static and dynamic), and average transmit power of BS. Other parameters are shown in Table VI.[1] Although a typical macro BS consumes low transmit power (10W-20W) compared to total power consumption of a BS (500W-2000W), the transmit power also exerts influence linearly on the power consumption of power amplifiers and cooling systems and battery backup and power supply loss in the BS. For example, we can show that power consumption of a macro BS can be reduced from 766W to 532W (234W saving) by just reducing transmit power from 20W to 10W in Fig. 1. Therefore, reducing the transmit power of BSs significantly contribute to save the total power consumption of BSs. Moreover, it is also helpful to reduce harmful effects of electromagnetic wave in humans. We will show that even with such a transmit power reduction, users can still expect high performance as long as they are in the interference-limited region and appropriate power allocation and user scheduling algorithms are adopted. We call this '$greening\ effect$'.

Without considering BS greening, BS transmit output power constraints can be divided into two classes. One is physical constraint and the other is regulation constraint. The physical transmit output power constraint can be varied between 50W $\sim$ 200W depends on BS power amplifier's capabilities. The communication industry regulator of each country manages civil radio spectrum and regulate radio emission due to harmful effects on human health and interference to service on similar frequencies. The regulator has been established maximum licensed EIRP (Effective Isotropic Radiation Power)

[1] Transmit power dependent parameters are number of sectors, number of power amplifiers (PA) per sector, PA efficiency, BS cooling loss, battery backup and power supply loss. Transmit power independent parameter is signal processing overhead

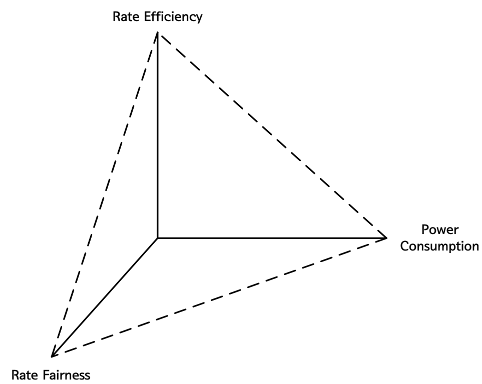


Fig. 2. The 3 axis of designing cellular network

which is the amount of power that a theoretical isotropic antenna would emit to produce the peak power density observed in the direction of maximum antenna gain. EIRP defined by following formula.

$$EIRP = \text{Tx output power}(dBW/dBm) + \text{Antenna gain}(dBi) - \text{Line loss}(dB) \tag{4}$$

Maximum licensed EIRP are 1600W in Ofcom (Office of Communications) which is regulator of UK and 2000W in FCC (Federal Communications Commission) which is regulator of US [9], [10]. These two transmit output power constraints are not average power but peak power.

There are rate efficiency, rate fairness and power consumption issues to design cellular networks in Fig. 2. So far, several papers have dealt with the tradeoff between rate efficiency and rate fairness in downlink cellular system [11]–[13]. However, very few attempts have been made at the tradeoff between rate efficiency-power consumption. Furthermore, transmit power constraints have been always constant values per each BS in the research of the tradeoff between rate efficiency-rate fairness. In this paper, we deal with tradeoff between rate efficiency-power consumption under several power constraints.

B. Related Work

The objectives of conventional radio resource management in single cell or multi cell downlink networks are almost rate adaptive, which focuses on throughput maximization with constant power constraints per each BS [14], [15] rather than margin adaptive [16], which focuses on power minimization with other constraints since BS power consumption relatively has not been a major concern. Especially, under long term utility maximization objectives, Venturino, L. $et\ al.$ [17] deals with interference management by adopting joint power allocation and user scheduling algorithms to maximize sum of utilities of users in multi-cell networks. However, the increasing interest on the BS power saving have led to that many papers have dealt with BS power saving schemes. There have been works dealing with BS on/off scheme that each BS turn on or turn off its operation along with long-term network traffic [1], [5], [6]. Moreover, Fehske, A. $et\ al.$ deals with the power saving effect with respect to cell size [8]. They defined area spectral efficiency and find optimal inter BS site distance to minimize area spectral efficiency when transmit power control is not adopted. Son, K. $et\ al.$ deals with joint base station operation and user association mechanism for energy-delay tradeoffs with time scale separation [7].

In greening works of other area, Tsiaflakis, P. $et\ al.$ [18], [19] shows the $greening\ effect$ in wired DSL (Digital Subscriber Line) networks. They show that when the power of all 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. Furthermore, they proposes fair-greening frameworks related to achievable rate and power fairness point of view. These papers are based on [20], which deals with power control algorithm to mitigate crosstalk of DSL networks which is regarded as specialized networks of wireless multi-cell networks, 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 consideration in greening of wireless multi-cell cellular networks than wired DSL networks due to adding user scheduling and stochastic channel variation in the cellular systems, there has been no study dealing with short-time scale (few msec or sec) or instantaneous greening design issue of BS power that people are wondering how to reduce transmit power of the BS with given BS power budget.

The main contributions of this paper are as follows.

1) We suggest four BS power sharing policies related to spatial and temporal sharing of BS total power and their frameworks. Our key idea is that if we can get little more performance gain by sharing BS total power budget spatially or temporally, we can achieve great power saving in terms of long-term network-wide BS power due to characteristic of '$greening\ effect$'. In other words, since we can expect small degradation in terms of network performance (fairness and throughput) when saving a lot of BS total power, spatial or temporal BS power sharing policies are very helpful to reduce long-term networkwide BS total power while achieving same network performance.
2) We present near (or sub) optimal power allocation and user scheduling algorithms per each time slot. Since we suggest long-term BS power budget, we introduce virtual queue concept per each time slot reflecting average power constraint. Furthermore, we deal with hierarchical lagrangian

multipliers in order to consider network-level and cell-level power constraint simultaneously.

3) The extensive greening evaluations are shown under a conventional regular hexagonal cell topology as well as irregular real Machester city, UK (United Kingdom) BS topology. We verify that up to 35% of total network BS power can be saved when applying spatio-temporal power sharing policies in asymmetric user distribution and regular hexagonal cell topology. Besides, we show more outstanding greening impact of applying spatio-temporal power sharing policies under irregular real cell topology. Furthermore, our greening framework can give 5.84 times GAT performance and 4.97 times greening efficiency when several micro BSs serve same coverage than macro BSs under same power consumption.

C. Paper Outline

In this paper, we aim at reducing BS power consumption with four greening power sharing policies and analyzing its impact on the multi-cell multi-carrier cellular networks. The following three sections are of our special interest:

1) **Greening Effect**
   - Equal power allocation case
   - Interference management case
2) **Spatial and Temporal Sharing of Transmit Power on Greening**
   - Q1. How we distribute given BS power budget to each BS?
   - Q2. How we utilize long-term BS power budget?
3) **Greening Evaluation**
   - Rate-power tradeoff
   - Small cell effect
   - Real BS deployment

In section II, we define '*greening effect*' and '*SINR ratio*'. Then, we give a simple example to explain greening effect. Furthermore, we compare greening effect of interference management (IM) and equal power allocation (EQ) case.

In section III, we analyze the impact of temporal and spatial power sharing policies. And then, we present long-term utility maximization problem with various power constraints given a fixed proportional fair scheduling. The power constraints have variable β which is the required power reduction with respect to full BS power usage. In order to find solution of this problem with various power constraints, we present appropriate power allocation and user scheduling algorithms.

In section IV, we present extensive evaluation in the several scenarios. First of all, we evaluate and compare GAT performance of four proposed frameworks and EQ along with different greening factor β. Second, we evaluate and compare greening performances of 4 greening frameworks in the real UK BS deployment and transmit power scenarios. Finally, we evaluate the small cell effect on greening in different cell size scenarios.

In section V, we conclude this paper.

II. Greening Effect on Multi-cell Multi-carrier Cellular Networks

A. System Model

1) 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 respectively. Each user can be associated with single BS. Denote by $\mathcal{K}_n$ the set of users associated with the BS n. i.e., $\mathcal{K} = \mathcal{K}_1 \cup \cdots \cup \mathcal{K}_N$ and $\mathcal{K}_n \cap \mathcal{K}_m = \emptyset, n \neq m$. All of the adjacent BSs can communicate with each other via high-speed wired dedicated hackhauls directly or through a 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 here 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 subcarriers, and each BS can use all the subchannels for data transmissions, i.e., universal frequency reuse.

2) Resource and Allocation Model: We consider the time-slotted system indexed by $t = 0, 1, \ldots$. During a slot, we assume that the channels are invariant, and 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. Reflecting the constraint that at most only one user can be selected in each subchannel for each BS, we should have:

$$\sum_{k \in \mathcal{K}_n} I_s^{k,n} \leq 1. \tag{5}$$

Let p_s^n be the transmit power of BS n on subchannel s, and let $\boldsymbol{p}_s \doteq [p_s^1, \dots p_s^N]^T$, and $\boldsymbol{p}^n \doteq [p_1^n, \dots p_S^n]^T$. There exists a maximum level of transmit power at each BS due to a hardware constraint (e.g., limit of BS amplifier capability) or regulations from government agencies due to harmful effect to humans. We will consider additional power constraints that we control for various power sharing policies, which we will present in the next section.

3) Link Model: We do not consider interference cancelation techniques, and hence a user treats the sum of received signal powers from other BSs as noise in each subchannel. We have interest on finding multi-carrier power allocation of each BS to mitigate these interferences. 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

$$SINR_s^{k,n}(\boldsymbol{p}_s) = \frac{g_s^{k,n} p_s^n}{\sum_{m \neq n} g_s^{k,m} p_s^m + \sigma_s^k}, \tag{6}$$

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 [21], the potential data rate of user k associated with BS n on subchannel s is given by

$$r_s^{k,n}(\boldsymbol{p}_s) = \frac{B}{S} \log_2 \left(1 + \frac{1}{\Gamma} SINR_s^{k,n}(\boldsymbol{p}_s) \right), \tag{7}$$

where B and Γ are the bandwidth and the SINR gap to capacity which is a function of bit error ratio (BER), coding gain and noise margin. 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 other 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 Γ and B/S throughout the paper.

B. Analysis

We define "*greening effect*" : the relative performance when transmit power is reduced. Also we define "*SINR ratio*" (SR) : the ratio of SINR with reduced transmission power of BS to SINR with full transmit power of BS when we equally reduce proportion of transmit power of all BSs, i.e.,(**Single Subcarrier Case**) :

$$SINR(\alpha) = \frac{\boldsymbol{g}^n P^{n,max}\alpha}{\boldsymbol{\sigma} + \sum_{m \neq n} \boldsymbol{h}^m P^{m,max}\alpha}, \tag{8}$$

$$SR(\alpha) = \frac{SINR(\alpha)}{SINR(\alpha = 1)} = \frac{1 + \boldsymbol{h}}{1/\alpha + \boldsymbol{h}}, \tag{9}$$

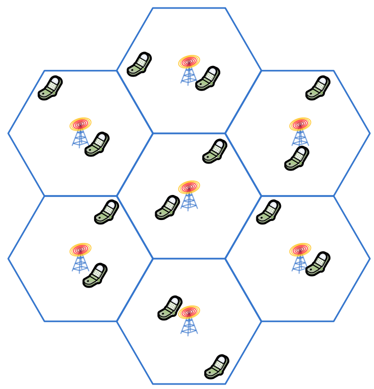
where

$$\boldsymbol{g} := \frac{\boldsymbol{g}^n P^{n,max}}{\boldsymbol{\sigma}}, \boldsymbol{h} := \frac{\sum_{m \neq n} \boldsymbol{h}^m P^{m,max}}{\boldsymbol{\sigma}}, \tag{10}$$

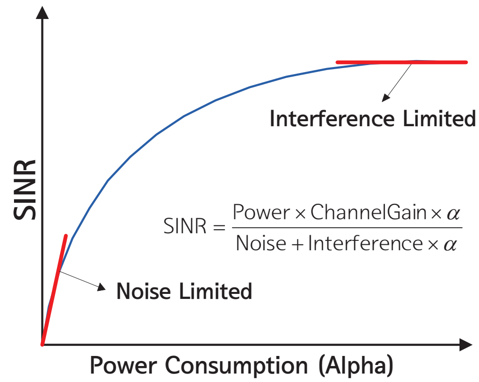
$\boldsymbol{g}$, $\boldsymbol{h}$ are noise normalized received power from BS n, noise normalized received interference from other BSs except for BS n, respectively. And α means required transmit power reduction with respect to full transmit power usage ($P^{n,max}$). From above equation (9), SR does not depend on $\boldsymbol{g}$, but depend on $\boldsymbol{h}$. So in Fig. 3(a), we can show that SR of near user from the center of the cell (center user) is less than near user from the edge of the cell (edge user). With this SR concept, we consider greening gain in multi-cell cellular network. There are interference limited region and noise limited region in Fig. 3(b), SINR graph. Also, There are high SINR region and low SINR region in Fig. 3(c), achievable rate graph. Although we dramatically reduce the transmit power, if we find operating point in the interference limited region or high SINR region, we can achieve relatively small performance degradation as compared with reducing transmit power, i.e., we can achieve high $greening\ effect$. We consider about the $greening\ effect$ of center user and edge user cases. Generally, center user achieve high SINR whereas edge user relatively cannot achieve high SINR. Since operating point at the high SINR is insensitive in the Fig. 3(c), center user can achieve high $greening\ effect$. Conversely, edge user receives high interference because of relatively near distance from neighbor cell BS compared to the center user. So edge user relatively achieves low SINR in Fig. 3(c). Thus we may think edge user cannot achieve high $greening\ effect$. However, because the noise term is independent with respect to the α, SR of center user is less than edge user, i.e., edge user operates at the interference limited region in Fig. 3(b). Since operating point at the interference limited region is insensitive in the Fig. 3(b), edge user can also achieve high $greening\ effect$.

III. Equal Power Allocation and Interference Management

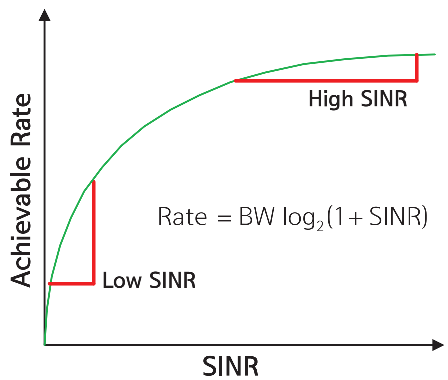
Although we examine $greening\ effect$ of single subcarrier case by SR formula, to optimize the network throughput on multi-cell cellular networks, we should consider inter-cell interference (ICI) management scheme by effectively controlling transmit power. In order to compare $greening\ effect$



(a) 7 cell cellular networks with center user and edge user



(b) SINR vs. power consumption (α)



(c) Achievable rate vs. SINR

Fig. 3. Conceptual description of greening effect

of equal power allocation case (EQ) and ICI management case (IM), we present simple simulation for same scenario as previous section in Fig. 3(a). In this simulation, we use 8 subcarrier and maximum 10W transmit power. The EQ allocates power equally all of the subcarrier, whereas the IM allocates power channel adaptively per each subcarrier. We expect the average throughput of center users and edge users in EQ are high. However, because BS control the transmit power to effectively mitigate interference on each user in the IM, we expect that the edge users is relatively not located in interference limited region. In table I, although SR of center user and edge user in IM is lower than EQ, the users can maintain high throughput when transmit power is reduced to 2W since the users are located in higher SINR region than EQ in Fig. 3(c). Therefore, we can expect high *greening effect* in the IM as well as EQ.

In the next section, we consider short-time scale greening under several power sharing policies.

TABLE I

SIMPLE SIMULATION RESULT OF *greening effect*

	Tx power	Center user rate		Center user SINR		Edge user rate		Edge user SINR	
Equal power allocation case	2W	6.99Mbps	92%	6574	78.2%	734.7kbps	83.4%	5.55	81.27%
	10W	7.56Mbps		8405		882.87kbps		6.8	
ICI management case	2W	5.87Mbps	97.2%	274.63	40.48%	2.35Mbps	76.3%	74.39	45.8%
	10W	6.04Mbps		678.34		3.08Mbps		162.3	

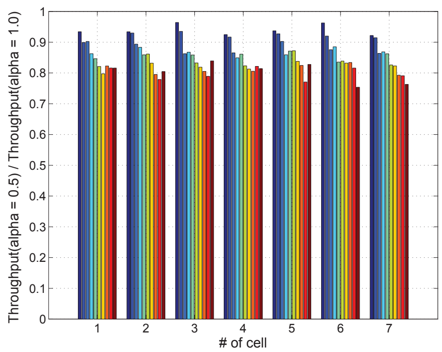


Fig. 4. Throughput ratio α = 0.5 to α = 1.0 per user

IV. IMPACT OF SPATIAL AND TEMPORAL POWER SHARING POLICIES

In this section, we introduce greening regulation. Under the greening regulation by government or policy of wireless service provider (WSP), our objective is to reduce BS power while maintaining high user throughput.

A. Greening Regulation

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 to 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. 5 shows 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.

B. Spatial and Temporal Power Sharing Policies

We consider following four greening power sharing policies.

1) *Cell-level and instantaneous power constraint (no power sharing)*
$\sum_s A_n p_s^n(t) + B_n \leq \beta \hat{P}^{n,max}, \forall n \in \mathcal{N},$
2) *Cell-level and time average power constraint (only temporal power sharing)*
$$\lim_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \sum_{s} A_n p_s^n(\tau) + B_n \leq \beta \bar{P}^{n,max}, \forall n \in \mathcal{N},$$
3) *Network-level and instantaneous power constraint (only spatial power sharing)*
$$\sum_n \Big(\sum_s A_n p_s^n(t) + B_n \Big) \leq \beta \hat{P}^{max}, \qquad \hat{P}^{max} = \sum_n \hat{P}^{n,max},$$
4) *Network-level and time average power constraint (spatio-temporal power sharing)*
$$\lim_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \sum_{n} \Big(\sum_{s} A_n p_s^n(\tau) + B_n \Big) \leq \beta \bar{P}^{max}, \qquad \bar{P}^{max} = \sum_n \bar{P}^{n,max}$$

The A_n and B_n are for modeling BS operational power consumption [22], 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 power budget. Irrespective of sharing policies, the basic transmit power constraints regulated by the hardware as well as the government agencies is imposed by $p_s^n(t) \leq \hat{p}^{n,licensed}$. Each power sharing policy can be classified into *network-level* and *cell-level* power constraints spatially, and *time average* and *instantaneous* power constraints temporally. We share the power budget of all BSs in *network-level* power constraint whereas we independently use the power budget of each BSs in *cell-level* power budget. Moreover, we use the power of BSs to adjust long-term average power per each time slot in *time average* power budget whereas we use the fixed power budget of BSs per each time slot in *instantaneous* power budget. Although sum of power budget in the entire network is same for all power budget, *network-level* power budget can exploit spatial degree of freedom under irregular BS topology and asymmetric user distribution, *time average* power budget can exploit temporal degree of freedom under stochastic channel variation. Therefore, under the same greening regulation, we can expect more throughput performance as long as we exploit spatial and temporal sharing of power than using fixed transmit

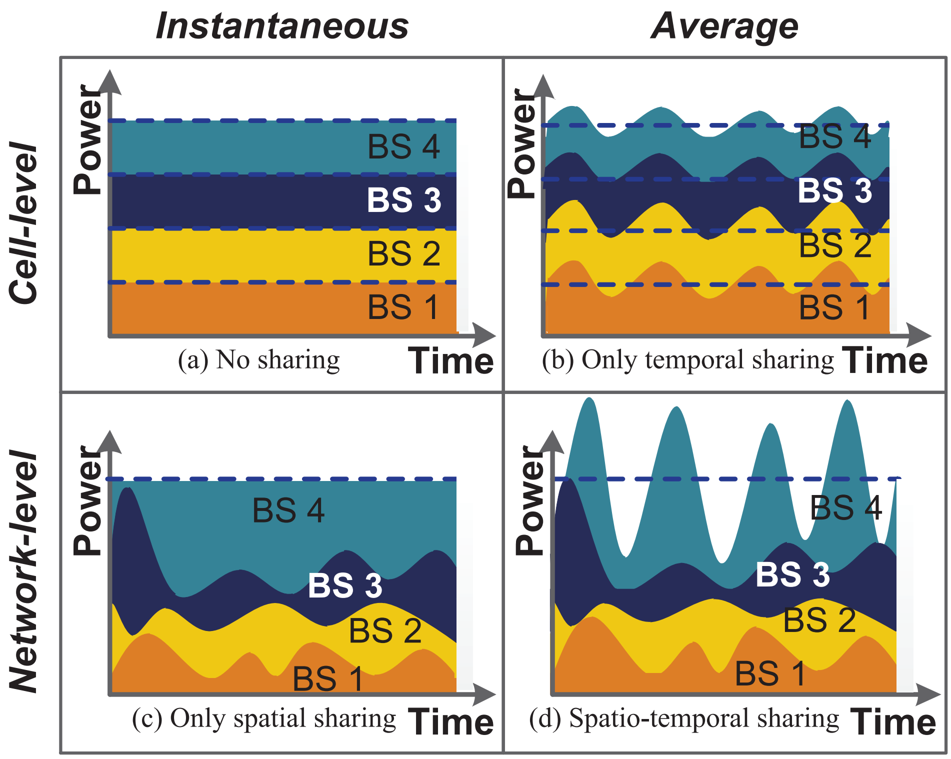


Fig. 5. Four greening power sharing policies

power per BS.

1) General Problem Statement: Our practical objective is to come up with the solution of following optimization problem by developing joint power allocation and user scheduling pair $(\boldsymbol{p}(t), \boldsymbol{I}(t))_{t=0}^{\infty}$, where $\boldsymbol{p}(t) \doteq (p_s^n, n \in N, s \in S)$ and $\boldsymbol{I}(t) \doteq (I_s^n, n \in N, s \in S)$ for each time slot when the original optimization problem is presented as follows:

$$(\textbf{Long-term P}): \quad \max \quad \sum_{n\in\mathcal{N}} \sum_{k\in\mathcal{K}_n} U_k(R_k) \tag{11}$$

$$\text{subject to} \quad \boldsymbol{R}(\beta) \in \mathcal{R} \tag{12}$$

where $U_k(R_k)$ is the long-term utility function of user k which is continuously differentiable and strictly increasing concave function. The set $\boldsymbol{R}(\beta)$ is the set of achievable long-term throughput of users along with greening factor β, referred to as rate region made by four greening constraints. A power sharing policy is reflected in the above optimization framework as a constraint. The power budget constraints of four different power sharing policies. To refer to each power sharing policy, we henceforth use the notation (S,T) = {(0,0), (0,1), (1,0), (1,1) }.

Then, we develop joint power allocation and user scheduling algorithms which achieve asymptotically near optimal solution of the optimization problem. Naturally, there are the tradeoff between β

and achievable rate region, i.e., as the power consumption is decrease, the achievable rate region also shrink. However, this tradeoff relationship can give us implications to design green cellular network due to varying greening effect according to the power budgets and network scenarios. In order to analyze tradeoff relationship between achievable rate and power consumption under several power budget constraints of cellular network, we formulate green cellular network frameworks. The four green cellular network frameworks and solutions are summarized in table II.

TABLE II
OVERVIEW OF GREEN CELLULAR NETWORK FRAMEWORKS AND SOLUTIONS

	Original framework	Slot-by-slot framework	Power allocation & User scheduling	Description
Greening 1	(13), (14), (15)	(21)(AVE = 0), (22), (14), (15)	(42)(V = 0), (43), (44), (46), (48)(V = 0)	Cell-level power constraint Instantaneous power constraint
Greening 2	(13), (14), (17)	(21)(AVE-PC), (22), (23), (26)(PC), (27)	(42)(V-PC), (43), (44), (45), (48), (49)(V-PC)	Cell-level power constraint Average power constraint
Greening 3	(13), (14), (16), (19)	(21)(AVE = 0), (22), (23), (25)	(42)(V-IPN), (43), (44), (45) (47), (48), (49)(V-IPN)	Network-level power constraint Instantaneous power constraint
Greening 4	(13), (14), (18) (20)	(21)(AVE-PN), (22), (23), (26)(PN), (28)	(42)(V-PN), (43), (44), (45) (48), (49)(V-PN)	Network-level power constraint Average power constraint

We consider long-term utility maximization frameworks with network-level and cell-level power budgets, instantaneous and time average power budgets. Long-term utility maximization problems are presented as follows : (**Long-term Utility Maximization Framework**):

$$\max \quad \sum_k U_k(R_k), \tag{13}$$

$$\text{subject to} \quad \sum_s p_s^n(t) \le \hat{p}^{n,licensed}, \forall n \in \mathcal{N}, \tag{14}$$

$$\sum_s A_n p_s^n(t) + B_n \le \beta \hat{P}^{n,max}, \forall n \in \mathcal{N}, \tag{15}$$

$$\sum_n \Big(\sum_s A_n p_s^n(t) + B_n \Big) \le \beta \hat{P}^{max}, \tag{16}$$

$$\lim_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \sum_s A_n p_s^n(\tau) + B_n \le \beta \bar{P}^{n,max}, \forall n \in \mathcal{N}, \tag{17}$$

$$\lim_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \sum_n \Big(\sum_s A_n p_s^n(\tau) + B_n \Big) \le \beta \bar{P}^{max}, \tag{18}$$

$$\hat{P}^{max} = \sum_n \hat{P}^{n,max}, \tag{19}$$

$$\bar{P}^{max} = \sum_n \bar{P}^{n,max}, \tag{20}$$

where $\hat{P}^{n,max}$, $\hat{P}^{max}$, $\bar{P}^{max}$, and $\bar{P}^{n,max}$ are maximum peak power budget of BS n, maximum peak power budget of entire network, maximum time average power budget of entire network and maximum time average power of BS n respectively. A_n and B_n are dependent and independent parameters with transmit power in power consumption model (1) of BS n. β is greening factor of BS per each cell. η is a parameter which reflects maximum licensed instantaneous power constraint of each BS.

2) Power Allocation and User Scheduling Algorithms: For each power budgets, we present following four joint power allocation and user scheduling algorithms.

- *Instantaneous power budget algorithm* (Greening 1, Greening 3) : We develop different convex-approximation scheme from previous work [17] and double binary search power allocation for spatially different level power constraints in these algorithms.
- *Time average power budget algorithm* (Greening 2, Greening 4) : These algorithms are made based on greedy primal dual algorithm of Stoylar A.L. [23]. We apply same philosophy as greedy primal dual algorithm to our multi-cell optimization problem with time average power constraint. The power allocation and user scheduling solution of these algorithms achieve asymptotically near optimal solution of original optimization problem.

Although there also can be tradeoff issues between computational complexity and optimality for our algorithms, it is beyond the scope of this paper.

Long-term utility maximization problem can be interpreted as solving the following slot-by-slot optimization problem with the help of the stochastic gradient-based technique and greedy primal-dual technique in [23], [24] that achieves asymptotically optimal solution when we select the achievable rate and virtual queue vector which is updated by time average constraint at the beginning of each time slot, maximizing the sum of weighted rates minus weighted virtual queue where the weights are marginal utilities and small parameter multiplied by the power at each time slot respectively.

(**Slot-by-slot Framework**):

$$\max_{\boldsymbol{p},\boldsymbol{I}} \quad h(\boldsymbol{p},\boldsymbol{I}) = \sum_{k\in\mathcal{K}} w_k \sum_{s\in\mathcal{S}} r_s^{k,n}(p_s^n, I_s^n) - \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}} \text{AVE}(p_s^n), \tag{21}$$

$$\text{subject to} \quad \sum_{k\in\mathcal{K}_n} I_s^{k,n} \le 1, \forall n \in \mathcal{N}, s \in \mathcal{S}, \tag{22}$$

$$\sum_s p_s^n(t) \le \hat{p}^{n,licensed}, \forall n \in \mathcal{N}, \tag{23}$$

$$\sum_s A_n p_s^n(t) + B_n \le \beta \hat{P}^{n,max}, \forall n \in \mathcal{N}, \tag{24}$$

$$\sum_n \Big(\sum_s A_n p_s^n(t) + B_n \Big) \le \beta \hat{P}^{max}, \tag{25}$$

$$\text{AVE}(p_s^n) = \begin{cases} \gamma_1 p_s^n Q_n^{pc} & \text{for} \quad \text{PC}, \\ \gamma_2 p_s^n Q^{pn} & \text{for} \quad \text{PN}, \end{cases} \tag{26}$$

$$Q_n^{pc}(t+1) = \big[Q_k^{pc}(t) - \frac{\beta \bar{P}^{n,max} - B_n}{A_n} + \sum_{s\in\mathcal{S}} p_s^n\big]^+, \quad \forall \in \mathcal{N}, \tag{27}$$

$$Q^{pn}(t+1) = \big[Q^{pn}(t) - (\beta \bar{P}^{max} - \sum_n B_n) + \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}} A_n p_s^n\big]^+, \tag{28}$$

where w_k is the derivative of utility $\frac{dU_k(R_k)}{dR_k}|_{R_k=R_k(t)}$ corresponding to user k. Especially, if utility function of the user k is a logarithmic function, then w_k is equal to $1/R_k(t)$ and we can achieve proportional fairness among the users [25]. We assume that t is omitted in this slot-by-slot framework, power allocation and user scheduling solution for simplicity. AVE(p_s^n) reflects network-level and cell-level time average power constraints. Q_n^{pc}, Q^{pn} are virtual queues that reflect time average power budget of BS n, time average power budget of entire network respectively. PC, PN are cell-level and network-level time average power constraint respectively. γ_1, γ_2 are small parameters to determine convergence time to the average constraint and asymptotic optimality. The virtual queue controls instantaneous power allocation and user scheduling to keep track of time average power. For example, if time average power of a BS n so far is larger than time average power constraint, virtual queue of BS n is increased so that instantaneous power is lowered to keep time average power. Otherwise, virtual queue is decreased. Since this cellular network is OFDMA system, only one user can be allocated to one subcarrier per one cell. $[\cdot]^+$ is maximum value between 0 and $\cdot$.

We now present solution of the problem (**Slot-by-slot Framework**) finding joint power allocation and user scheduling pair $(\boldsymbol{p}(t), \boldsymbol{I}(t))_{t=0}^{\infty}$. Because the number of available joint power allocation and user scheduling combinations are infinitely many, we need to solve user scheduling problem under given power allocation and power allocation problem under given user scheduling problem iteratively until they converge at each time slot. Unfortunately, even though user scheduling is given, it is known in [26] 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. Accordingly, to find a global optimal solution, we need to fully search the space of the feasible powers for all BSs with a small granularity along with the possible combinations of user scheduling. Since optimal solution has high computational complexity, we use convex (concave) approximation scheme to our problem (**Slot-by-slot Framework**) to obtain near optimal solution.

For given power allocation, slot-by-slot framework can be decomposed into user scheduling issues at each cell.

Lemma IV.1. *If we assume that there is any given feasible power allocation $\boldsymbol{p}$, then optimization problem (**Slot-by -slot Framework**) given by (21)∼(28) can be reduced to $N \times S$ independent intra-cell optimizations for each BS n and subcarrier s.*

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

$$h(\boldsymbol{p},\boldsymbol{I}) = \sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{K}_n}\left[w_k \sum_{s\in\mathcal{S}} I_s^{k,n} \cdot r_s^{k,n}(\boldsymbol{p}_s) - \mathrm{AVE}(p_s^n)\right] = \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}}\left[\sum_{k\in\mathcal{K}_n} w_k \cdot I_s^{k,n} \cdot r_s^{k,n}(p_s) - \mathrm{AVE}(p_s^n)\right]. \tag{29}$$

Because w_k, $r_s^{k,n}(\boldsymbol{p}_s)$ and $\mathrm{AVE}(p_s^n)$ are given parameters, we only have to consider dependencies among $I_s^{k,n}$. Since the constraint (22) do not play a role across different BSs and subcarriers, the original problem is equivalent to independently solving the $N \times S$ subproblems for each BS and subcarrier. This completes the proof. ∎

Furthermore, for given user scheduling $\boldsymbol{I}$, the slot-by-slot framework is represented to the power allocation problem as follows:

$$\max_{\boldsymbol{p}} \quad \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}}\left[w_k \log_2\left(1+\frac{g_s^{k,n} p_s^n}{\sum_{m\neq n} g_s^{k,m} p_s^m + \sigma_s^k}\right) - \mathrm{AVE}(p_s^n)\right], \tag{30}$$

$$\text{subject to} \quad \sum_s p_s^n(t) \le \hat{p}^{n,licensed}, \forall n \in \mathcal{N}, \tag{31}$$

$$\sum_s A_n p_s^n(t) + B_n \le \beta \hat{P}^{n,max}, \forall n \in \mathcal{N}, \tag{32}$$

$$\sum_n \left(\sum_s A_n p_s^n(t) + B_n\right) \le \beta \hat{P}^{max}, \tag{33}$$

Since (34) is non-convex function, we take the convex approximation as follows.

$$\max_{\boldsymbol{p}} \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}}\left[w_k \log_2\left(1+\frac{g_s^{k,n}p_s^n}{\sum_{m\neq n} g_s^{k,m}p_s^m+\sigma_s^k}\right)-\mathrm{AVE}(p_s^n)\right], \tag{34}$$

$$= \max_{\boldsymbol{p}} \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}}\left[w_k \log_2\left(\sum_{m\in\mathcal{N}} g_s^{k,m}p_s^m+\sigma_s^k\right)-\log_2\left(\sum_{m\neq n} g_s^{k,m}p_s^m+\sigma_s^k\right)-\mathrm{AVE}(p_s^n)\right], \tag{35}$$

$$\geq \max_{\boldsymbol{p}} \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}}\left[w_k \log_2\left(\sum_{m\in\mathcal{N}} g_s^{k,m}p_s^m+\sigma_s^k\right)-\left(\sum_{m\neq n} a_s^{k,m}p_s^m+c_s^k\right)-\mathrm{AVE}(p_s^n)\right], \tag{36}$$

Although this approximation is similar to CA-DSB (Convex Approximation - Distributed Spectrum Balancing) algorithm [20] which is near optimal power allocation algorithm in DSL network since user scheduling $\boldsymbol{I}$ is given, we also should consider time average power constraint in the optimization problem at each time slot. Fortunately, since virtual queue which reflects time average power constraint is fixed during the time slot and $\mathrm{AVE}(p_s^n)$ is linear function of p_s^n, time average power constraint has not effect on the convexity (or concavity) of the optimization problem. Since the second term of (35) is non-concave (convex) while the first and third terms are concave and linear function, we approximate the part of the objective function by a lower bound hyperplane as above. 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 procedures under given approximation parameters $a_s^{k,m}$ $(\forall m)$ and $a_s^{k,m}$ $(\forall m)$ under given power allocation p_s^n $(\forall n, \forall s)$ iteratively until the power allocations are converged. By applying this lower bound approximation, (34) can be transformed into the following convex optimization problem:

$$\max_{\boldsymbol{p}} \quad \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}}\left[w_k \log_2\left(\sum_{m\in\mathcal{N}} g_s^{k,m}p_s^m+\sigma_s k\right)-\left(\sum_{m\neq n} a_s^{k,m}p_s^m+c_s^k\right)-\mathrm{AVE}(p_s^n)\right], \tag{37}$$

$$\text{subject to } \sum_s p_s^n(t) \leq \hat{p}^{n,licensed}, \forall n\in\mathcal{N}, \tag{38}$$

$$\sum_s A_n p_s^n(t)+B_n \leq \beta \hat{P}^{n,max}, \forall n\in\mathcal{N}, \tag{39}$$

$$\sum_n\left(\sum_s A_n p_s^n(t)+B_n\right) \leq \beta \hat{P}^{max}, \tag{40}$$

$$\tag{41}$$

For given user scheduling and above convex optimization problem, we derive power allocation by applying Karush-Khun-Tucker (KKT) conditions [27]. (**Power Allocation and User Scheduling**):

$$p_s^n = \left[\frac{w_n / \ln 2}{\lambda_n + V + tax_s^n} - \frac{\sum\limits_{m \neq n} g_s^{n,m} p_s^m + \sigma_s^n}{g_s^n} \right]_0^+, \tag{42}$$

$$tax_s^n = \sum_{m \neq n} w_m a_s^{n,m} - \sum_{m \neq n} w_m \frac{\frac{g_s^{m,n}}{\ln 2}}{\sum_p g_s^{m,p} p_s^p + \sigma_s^m}, \tag{43}$$

$$a_s^{m,n} = \frac{|h_s^{n,m}|^2 / \ln 2}{\sum_{q \neq n} |h_s^{n,q}|^2 p_s^q + \sigma_s^n}, \tag{44}$$

$$\lambda_n \Big(\sum_{s \in \mathcal{S}} p_s^n - \hat{P}^{n,licensed} \Big) = 0, \tag{45}$$

$$\lambda_n \Big(\sum_{s \in \mathcal{S}} A_n p_s^n + B_n - \beta \hat{P}^{n,max} \Big) = 0, \tag{46}$$

$$\mu \Big(\sum_{n \in \mathcal{N}} \Big(\sum_{s \in \mathcal{S}} A_n p_s^n + B_n \Big) - \beta \hat{P}^{max} \Big) = 0, \tag{47}$$

$$I_s^{k,n} = \begin{cases} 1, \quad \text{if} \quad k = \text{argmax}_{k \in \mathcal{K}_n} w_k r_s^{k,n}(p_s), \\ 0, \quad \text{otherwise}, \end{cases} \tag{48}$$

$$V = \begin{cases} \mu, \qquad \text{for} \quad \text{IPN}, \\ \gamma_1 Q_n^{pc}, \qquad \text{for} \quad \text{PC}, \\ \gamma_2 Q^{pn}, \qquad \text{for} \quad \text{PN}, \end{cases} \tag{49}$$

where tax_s^n is a taxation term which reflects that the power of BS in the cell will give interferences to the scheduled users in the neighboring cell. For example, if allocated power at the BS is so much that interferences to the scheduled users in the neighboring cell are high, taxation term is higher, and allocated power is lower inversely to mitigate interference. If taxation term is zero, above power allocation algorithm is water-filling type [28], which only consider interference from BSs in other cell. IPN is network-level instantaneous power constraint. Assume that all information 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 centralized base station controller (BSC). λ_n and μ are non-negative Lagrange multipliers related to the cell-level and network-level instantaneous BS power budget constraint (14), (15) and (16), and these two multipliers must be chosen so that complementary slackness conditions (45) $\sim$ (47) are satisfied respectively. Given all other parameters, closed form equation of p_s^n in (42) is a function of λ_n and μ. Since there are two variables in the closed form equation (42), we cannot directly solve by a fast bisection method. Therefore, we consider three cases according to the conditions of λ_n and μ as follows:

1) *Cell-level BS power budget limited case* ($\lambda_n > 0$ and μ = 0): p_s^n is a monotonic function of λ_n. This case is the same as the classical bisection method. This case can be occurred only when we have not network-level instantaneous power budget.
2) *Network-level power budget limited case* (λ_n = 0 and $\mu > 0$): p_s^n is a monotonic function of μ. This case is also the same as the classical bisection method. This case can be occurred when allocated power on BS n is below than its cell-level power budget.
3) *Both limited case - double binary search* ($\lambda_n > 0$ and $\mu > 0$): p_s^n is a function of λ_n and μ. In this case, we solve a monotonic function of λ_n under given μ, a monotonic function of μ under given λ_n iteratively until the p_s^n converges to the some point with error margin. This case can be occurred when we fully use the cell-level power budget and network-level power budget at the same time.

Starting from the initial power allocation and λ_n and μ, we can calculate p_s^n for all subcarriers and BSs. If the sum of updated p_s^n of BS n or total network is exceeds $\hat{P}^{n,max}$ or $\hat{P}^{max}$ respectively, then λ_n or μ are increased. otherwise, λ_n or μ are decreased. We iteratively repeat calculation of p_s^n until (45) $\sim$ (47) are satisfied.[2] User is selected depending on the weight of user and achievable rate for each time slot. BS and BSC algorithms are given by table III for each BS instantaneous power constraints (Greening 1, Greening 2, Greening 4), and table IV for total BS instantaneous power constraint (Greening 3).

C. Cost of Power Sharing Policies

We now discuss the implementation cost of the power sharing policies ((S,T) = (1,0) , (0,1) , (1,1)) compared to no sharing ((S,T) = (0,0)), from the *(i)* algorithmic and *(ii)* transmit power usage perspectives. In the algorithmic point of view, in order to calculate power allocation (**??**) 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 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.

[2]Actually, λ_n and μ cannot reach until zero because of nature of the bisection method. Therefore, if λ_n or μ is sufficiently small as compared with tax, we assume that λ_n and μ are zero respectively.

TABLE III
GREENING 1,2,4 ALGORITHM DESCRIPTION

BS Algorithm

Virtual queues update & exchange
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 (42)
      if $\sum_s p_s^n > \beta \hat{P}^{n,max} \eta$ 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

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 $\boldsymbol{I}$ of all BSs converge or max # of iterations is reached

Moreover, in 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 from the United Kingdom [9] or FCC from the United States [10]. Although we cannot fully share the total BS power when we obey these constraints, we can obtain substantial power sharing gain without additional cost (e.g., power amplifier upgrade or penalty of over usage of transmit power).

V. GREENING EVALUATION

Now we evaluate the performance of proposed greening frameworks under various simulation topologies and scenarios. As the first step in our simulation, we verify characteristics of rate-power tradeoff of proposed frameworks and conventional equal power allocation with no power sharing (EQ) in a two-tier macro-cell network composed of hexagonal regular 19 cells. Second, we verify previous results in a real BS deployment topology of UK (United Kingdom) in order to show more realistic greening evaluation results. Finally, we analyze greening effects of our frameworks with network-level and average power constraint which achieve the best performance out of our frameworks with different cell sizes and compare them with EQ at the same network topology.

TABLE IV
GREENING 3 ALGORITHM DESCRIPTION

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 = (μ^{min}+μ^{max})/2, for each BS, λ_n^{min}, λ_n^{max} decision
    while
      λ_n = (λ_n^{min}+λ_n^{max})/2
      Taxation update from (43), update p_s^n from (42), $\forall s$
      send p_s^n, $I_s^{k,n}$ to each BS n, $\forall s$, $\forall n$, receive int_s^n, g_s^n, W_n from each BS n, $\forall s$, $\forall n$
      if $\sum_s p_s^n > P^{n,tot}$ 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 $\sum_n \sum_s p_s^n > \beta \sum_n P^{n,max} \eta$ 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

A. Rate-power Tradeoff under Regular BS Deployment

We consider a two-tier macro-cell network composed of hexagonal 19 cells. Wrap around techniques are applied in the cells for the same interference environment. We refer to the parameters on OFDMA cellular networks from 802.16m standard document [29]. Each BS use 8 subcarriers and 20W maximum instantaneous transmit power when instantaneous cell-level power constraint is applied, 40W maximum instantaneous transmit power when other power constraints are applied. The power consumption model of BS was introduced in (1). There are linearly dependent terms with transmit power and independent terms with transmit power. Within the simulation time, we assume that all users are respectively associated in each cell and do not have mobility. Although radius of one cell is basically 2km, the radius can be changed in the small cell effect evaluation. Basically, proportional fair user scheduling is adopted (i.e., utility function of user is $\log(\cdot)$). 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 between BS and user. Noise figure of receiver antenna is added in thermal noise to show more accurate performance curve with greening factor β. Greening factor β is from 0.1 to 1.0 which are ratio of reduced power to full power. Summary of simulation parameters

TABLE V
SIMULATION PARAMETERS

· Number of subcarriers : 8
· Maximum tx power per each BS (instantaneous power constraint): 20W
· Maximum tx power per each BS (network-level or average power constraint): 40W
· Total network power budget : 14559W
· Number of BSs : 19
· Number of users per each cell: 10
· Radius of BS (Macro cell) : 2km
· α : 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
· Greening factor : 0.1 - 1.0

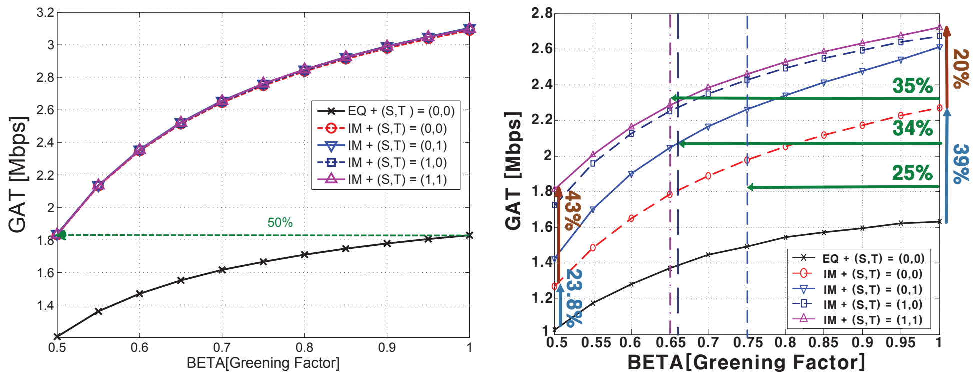
is given in Table V.

We define evaluation metrics so as to clearly identify the greening effect of given frameworks. The evaluation metrics are as follows :

1) **Geometric Average user Throughput (GAT)** : GAT is defined as geometric average throughput considering system objective. Although utility reflects fairness among the users, we cannot absolutely compare among different utilities since utility does not have a unit. In other hands, while sum of rates have a unit, it does not reflect fairness among users. For example, since center users achieve higher throughput than edge users, edge user throughput has less effect on sum of rates than center user throughput. GAT reflects not only actually comparable units but also fairness among users.
2) **Greening Efficiency [bps/Hz/joule]** : Greening Efficiency is defined as achievable rate per unit frequency per unit energy. This metric show that how we effectively use the BS power in terms of throughput with the given BS power constraint.

We verify the performance of proposed greening frameworks and EQ with greening evaluation metrics under two different user distribution. We consider 7 number of cells. First of all, we verify the four greening frameworks (Greening 1 $\sim$ Greening 4) in symmetric user distribution case. i.e., for each cell, 10 users are uniformly distributed (associated). Second, we generate different number of users and different user distribution per each cell. 10 users are deployed at near the center of $cell_1$ $\sim cell_3$, whereas 20 users are deployed at near the edge of $cell_4 \sim cell_7$. Other 12 cells are just give constant interference to the considering 7 cells in all of scenarios. Each BS of entire network practically cannot use unlimited instantaneous transmit power. Therefore, we assume that BS with network-level or average power constraints (Greening 2, Greening 3, Greening 4) can use instantaneous power to twice of maximum power constraint of BS with instantaneous power constraint (Greening 1). Fig. 4 shows the GAT of our greening frameworks and EQ in two different user distribution scenarios respectively. In the Fig. 6(a), there are no difference among our four frameworks whereas EQ and our frameworks show the big difference in terms of GAT. It shows that we can save 50% power with our frameworks compared to EQ. Since users are symmetrically distributed among cells, we can exploit only small spatial and temporal degree of freedom in our power budget. i.e., because all of users take proportional fair scheduling, all of them do not need any more power. However, in Fig. 6(b), there are two difference among four frameworks. First of all, we consider network-level and cell-level power constraint. Because users are very asymmetrically distributed and more users are in the edge cell than center cell, users in the edge cells may need more power budget whereas users in the center cells do not need any more power budget. If we use network-level power constraint, we can give more power to the users in the edge cells and they can achieve high throughput whereas cell-level power constraint cannot give more transmit power to the users in the edge cells. Second, we consider average and instantaneous power constraint. As the same reason of spatial power budget, edge users may need more power budget in the instantaneous power budget. However, by taking average power budget, even though we should give lower power to the normal users in other time slot, we can give more transmit power to the very poor users in that time slot and he or she can achieves more throughput than instantaneous power budget. Therefore, we can verify that the Greening 2 ((S,T) = (0,1)), Greening 3 ((S,T) = (1,0)), Greening 4 ((S,T) = (1,1)) save the total network-level power to 25%, 34%, 35% of power consumption of Greening 1 (No power sharing) in Fig 6(b) respectively. These results lead us to the conclusion that as user distribution is more asymmetric, spatial and temporal degree of freedom of power are more utilized and we can achieve more power saving under the (S,T) = (1,1) than other constraints.

Another observation in Fig.6(b) is that 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=0.1), spatio-temporal power sharing gain (i.e., increment if EQ to 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



(a) Symmetric user distribution

(b) Asymmetric user distribution and asymmetric number of users

Fig. 6. GAT of four Greening frameworks and equal power allocation with no power sharing

as the interference management gain (43%).

B. Real UK BS Deployment Simulation

In this section, we verify the greening performance of our greening frameworks under the part of the Manchester city (3km $\times$ 2.5km), real UK macro BS deployment scenario [9][3] in Fig. 7. We carry out our simulation for the Greening 1 (IM with no power sharing), Greening 4 (IM with (S,T) = (1,1)) frameworks and EQ with no power sharing under 15 number of BSs topology which are owned by T-Mobile wireless service provider (WSP). Maximum licensed instantaneous transmit power per each BS is 63W whereas each BS use different transmit power depends on BS location and user density. We assume that the deployment of BSs in the Manchester city is based on average user density. Therefore, we consider all of BSs in the network has same number of associated users. In this simulation, 10 number of users are associated in $cell_1 \sim cell_8$ respectively. Under instantaneous power constraint, a BS allocates power per each subcarrier considering interference from inter-cell BS in the Greening 1 framework. A BS allocates transmit power per each subcarrier of each BS with network-level average BS power constraint in the Greening 4 framework. Fig 8 shows difference of GAT among Greening 1, Greening 4 and EQ. Because Greening 1 mitigate interference from BSs of other cells, Greening 1 can achieve more performance than EQ. The interesting remark comes from difference of performance between Greening 1 and Greening 4 frameworks. In the previous regular 19 cell deployment simulation, we show the difference of GAT between frameworks with network-level, average power constraint and cell-level, instantaneous power constraint under asymmetric user distribution and our conclusion is that

[3]BS deployment and transmit power per each BS, maximum licensed transmit power per each BS information which is voluntarily given by wireless service operator of UK can be acquired from this website

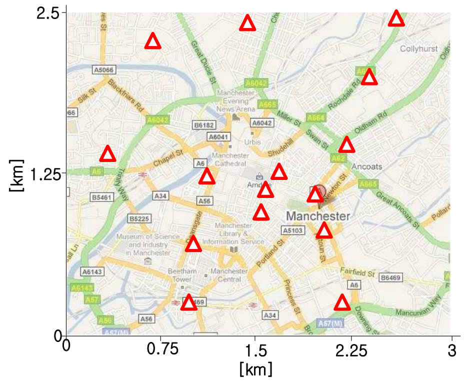


Fig. 7. BS deployment in Manchester city

as user distribution is more asymmetric, we can achieve more performance at the network-level and average power constraint than other power constraints. Since real BSs are very irregularly deployed, user distribution among cells in real environment is more asymmetric than regular BS deployment system. Therefore, Fig. 8 shows that framework with network-level spatio-temporal average power sharing (Greening 4) can achieve more than 200% GAT with full power budget than no spatio-temporal power sharing case (Greening 1).

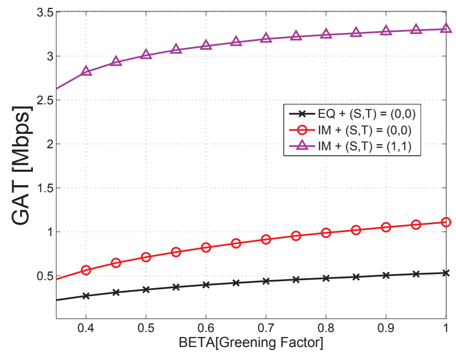


Fig. 8. GAT of three frameworks in Manchester city

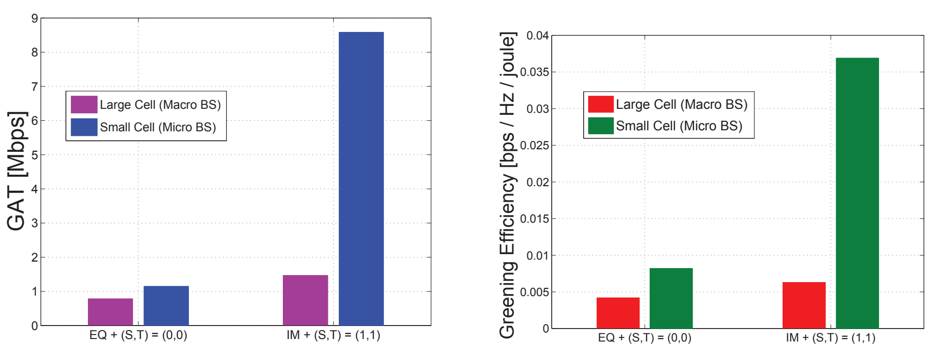
C. Small Cell (Micro BS) Greening Effect

As increasing demand of user data traffic in next generation networks, the coverage of BSs will be smaller and smaller to satisfy capacity demand. we consider about greening effect on the small cell (such as micro and femto cell) compare to the large cell. First, suppose that there are cells with radius d. And users are uniformly deployed in the cells. We consider $SINR\ ratio$ in section II. From the characteristic of path loss on wireless communication, h_j is in inverse proportion to square of distance from BS j to user n ideally (i.e., path loss exponent is 2). However, there are many multi-path signal due to scattering, reflecting, diffracting in real wireless communication environment. Therefore, path loss exponent depends on the propagation environment. From an empirical-based model that takes into account frequency and antenna heights at 900MHz and 1.9GHz, path loss exponent is about 3.7 $\sim$ 6.5 in urban macrocells [21]. However the coverage of the cell is in inverse proportion to square of radius. Thus, we can reduce the transmit power with maintaining SINR reduction when the cell is smaller in the same communication area. Therefore, inevitable trend of smaller cell on next generation cellular networks will give us more greening effect.

We evaluate the small cell greening performance at the two different cell sizes. First, we carry out the simulation with 1000m (large cell, macro BS), 354m (small cell, micro BS) cell radiuses. We use same total network BS power and same number of users and same user distribution at the same area for fairly observing small cell greening effect. We use 766.284W, 47.89W maximum average power of each macro and micro BS, 32, 2 users are uniformly distributed per each cell for large cell, small cell cases respectively. Power consumption model of micro BS is in equation (2), (3). We run our simulation for Greening 4 framework which has spatio-temporal power sharing policy with network-wide average power constraint and equal power allocation with no power sharing and show

TABLE VI
BASE STATION PARAMETERS

1	Macro BS Parameters
	· N_{sector} (Number of sectors): 1
	· N_{PApSec} (Number of power amplifiers per sector): 6
	· μ (Power amplifier efficiency) : 35
	· P_{SP} (Signal processing overhead) : 36.4W
	· C_C (Cooling loss) : 0.27
	· C_{PSBB} (Battery backup and power supply loss) : 0.11
2	Micro BS Parameters
	· μ (Power amplifier efficiency) : 20
	· $C_{TX,static}$ (Static tx power portion) : 0.8
	· $P_{SP,static}$ (Static signal processing) : 15W
	· C_{PS} (Power supply loss) : 0.11
	· $C_{TX,NL}$ (Dynamic tx power portion per link) : 0.04
	· $P_{SP,NL}$ (Dynamic signal processing per link) : 0.55W



(a) GAT vs. cell size

(b) Greening efficiency vs. cell size

Fig. 9. GAT and Greening efficiency under different cell sizes

the GAT and greening efficiency of different cell size cases. Fig. 9(a) clearly shows that when the micro BSs are used under the same resource environments (BS power consumption, user distribution, service coverage), achievable performance (GAT) of Greening 4 is more increased than EQ (484% in GAT). Fig. 9(b) clearly shows not only that greening efficiency of Greening 4 is greater than EQ but also that as the cell size decease, increment of greening efficiency of Greening 4 is greater than EQ (497% in greening efficiency). The reason why this small cell effect is seen is that as the cell size decrease, all of users in the network suffer from more severe interference from the other cells. Since Greening 4 framework effectively mitigate interference, it can achieve more performance increment in small cell deployment than EQ which cannot manage interference from other neighboring BSs.

VI. CONCLUSION

This paper dealt with short-time scale BS greening on multi-cell cellular networks. In the first part, we considered *greening effect* of cellular networks. We verified that the high *greening effect* is achieved in the ICI management case as well as the equal power allocation case for all of users in the network. Second, we proposed network-level greening frameworks with various power budget constraints and develop their power allocation and user scheduling algorithms. Through the extensive greening evaluation, we showed that WSP can save significant average power of BS. First of all, the result clearly showed that spatio-temporal power sharing with network-level average power constraint (Greening 4) can save 35% network-level total power under asymmetric user distribution case rather than no spatio-temporal power sharing (Greening 1) because it fully exploits the spatial and temporal degree of freedom of power of BSs. Second, through real BS deployment in the part of Manchester city simulation, we found that real irregular BS deployment helps throughput increment (200%) of spatial and temporal power sharing. Fourth, we examined the tradeoff between fairness-greening effect when different fairness criterions are adopted in our frameworks. Finally, we analyzed economic point of view of green cellular networks and the analysis results concluded that WSPs are willing to reduce their transmit power to maximize their surplus. Finally, our Greening 4 framework show outstanding greening performance increment (484% in GAT, 497% in greening efficiency) when micro BSs are used than case that macro BSs are used under same service coverage, network-wide long-term BS power consumption, user distribution environments. This results lead us to the conclusion that power allocation and user scheduling considering interference management and spatio-temporal power sharing can be obtain more truly magnificent greening performance than equal power allocation with no power sharing case at the small cell which is an inevitable trend with heterogeneous network in the next generation cellular network to maximally exploit the spectral resource.

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