Interference-Aware Energy-Efficient Power Optimization*

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***Abstract*—While the demand for battery capacity on mobile devices has grown with the increase in high-bandwidth multimedia rich applications, battery technology has not kept up with this demand. Therefore power optimization techniques are becoming increasingly important in wireless system design. Power optimization schemes are also important for interference management in wireless systems as interference resulting from aggressive spectral reuse and high power transmission severely limits system performance. Although power optimization plays a pivotal role in both interference management and energy utilization, little research addresses their joint interaction. In this paper, we develop energy-efficient power optimization schemes for interference-limited communications. Both circuit and transmit powers are considered and energy efficiency is emphasized over throughput. We note that the general power optimization problem in the presence of interference is intractable even when ideal user cooperation is assumed. We first study this problem for a simple two-user network with ideal user cooperation and then develop a practical non-cooperative power optimization scheme. Simulation results show that the proposed scheme improves not only energy efficiency but also spectral efficiency in an interference-limited cellular network.**

I. Introduction

As more users need to share the same spectrum for wideband multimedia communications and cellular networks move towards aggressive full frequency reuse scenarios, the performance of wireless cellular networks is heavily impaired by interference. This motivates the use of multi-cell power control optimization for interference management. Power optimization is also extremely important for reducing energy consumption for mobile devices. In this case, as higher capacity wireless links are designed to meet increasing demand from multimedia applications, the device power consumption also increases. In contrast, the improvement in battery technology is much slower, leading to an exponentially increasing gap between the required and available battery capacity [1]. Hence, power optimization is also important for maximizing the battery life for mobile devices. Although, power optimization plays a pivotal role in both interference management and energy utilization, little research has addressed their joint interaction. In this paper, we are addressing this joint limitation and investigates energy-efficient power optimization, specifically for interference limited environments.

Our previous work in [2]–[5] has studied uplink energy-efficient communications in single-cell *orthogonal frequency division multiple access* (OFDMA) systems to improve mobile battery consumption. Using throughput per Joule as a performance metric, we have studied both link adaptation and resource allocation techniques, which emphasize *energy efficiency* (EE) over throughput. We have observed that in an interference free environment, a tradeoff between EE and *spectral efficiency* (SE) exists, as increasing transmit power always improves throughput but not necessarily EE. In this paper, we continue our investigation to consider multi-cell interference-limited scenarios and develop power control and resource allocation schemes to improve EE. Our schemes are shown to not only improve system EE but also to reduce the EE-SE tradeoff due to the conservative nature of power allocation, which effectively controls other-cell interference to improve network throughput.

The rest of the paper is organized as follows: We first formulate the interference aware power control problem in Section II. In Section III, a two-user network with ideal user cooperation is discussed to gain insights into energy-efficient power control. We develop a non-cooperative energy-efficient power control scheme in Section IV and demonstrate performance improvement with simulations in Section V. Finally, we conclude the paper in Section VI.

II. Problem Description

In this section, we introduce the concept of interference-aware energy-efficient power control.

Consider a system with K subchannels that experience frequency-selective fading and *additive white Gaussian noise* (AWGN). There are N users, each consisting of a pair of transmitter and receiver, operating on these subchannels. Accurate channel state information is known to any transmitter and receiver. Denote the signal power attenuation of User i at Subchannel k to be $g_{ii}^{(k)}$ and the interference power gain from the transmitter of User i to the receiver of User j at Subchannel k to be $g_{ij}^{(k)}$. The noise power on each subchannel is σ^2. The power allocation of User n on all subchannels is denoted by vector $\mathbf{p}_n = [p_n^{(1)} p_n^{(2)} \cdots p_n^{(K)}]$. The *signal-to-interference-plus-noise ratio* (SINR), $\eta_n^{(k)}$, of User n at Subchannel k is

$$\eta_n^{(k)} = \frac{p_n^{(k)} g_{nn}^{(k)}}{\sum_{i=1, i\neq n}^{N} p_i^{(k)} g_{in}^{(k)} + \sigma^2}. \quad (1)$$

The data rate at Subchannel k of User n is $r_n^{(k)}$ and

$$r_n^{(k)} = R(\eta_n^{(k)}), \quad (2)$$

where $R()$ is the data rate function and depends on the modulation and coding used. $R()$ is assumed to be strictly concave and increasing. By default, we assume capacity approaching coding and $r_n^{(k)} = w \log(1 + \eta_n^{(k)})$, where w is the bandwidth of each subchannel.

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Let the data rate vector of User n across the K subchannels be $\mathbf{r}_n = [r_n^{(1)}, r_n^{(2)}, \cdots, r_n^{(K)}]^T$, then the overall data rate is

$$r_n = \sum_{k=1}^{K} r_n^{(k)}. \tag{3}$$

The total transmit power is

$$p_n = \sum_{k=1}^{K} p_n^{(k)}. \tag{4}$$

Note that as in [2], [3], both transmit power and circuit power, p_c, are important for energy-efficient communications. While transmit power is used for reliable data transmission, circuit power represents average energy consumption of device electronics.

For energy-efficient communications, it is desirable to maximize the amount of data sent with a given amount of energy. Hence, given any amount of energy $\triangle e$ consumed in duration $\triangle t$, i.e. $\triangle e = \triangle t(p_n + p_c)$, User n wants to send a maximum amount of data by allocating transmit power to maximize $\frac{r_n \triangle t}{\triangle e}$, which is equivalent to maximizing

$$u_n = \frac{r_n}{\triangle e / \triangle t} = \frac{r_n}{p_n + p_c}. \tag{5}$$

u_n is called EE for User n. The EE of the overall network is

$$u = \sum_{n=1}^{N} u_n, \tag{6}$$

which is a function of $p_n^{(k)}$ for all n and k. We now need to determine power allocations of all users to optimize overall network EE subject to the interference scenario.

III. Cooperative Two-User Case

Note that the solution maximizing sum network EE is difficult to obtain as the objective function, in general, is non-concave in $p_n^{(k)}$. To simplify the problem and gain some insight, in this section we investigate the case where two users transmit simultaneously on a single channel in this section. We assume both users have complete network knowledge and cooperate to maximize

$$u(p_1, p_2) = \frac{r_1}{p_1 + p_c} + \frac{r_2}{p_2 + p_c}, \tag{7}$$

where $r_1 = w\log(1+\frac{p_1 g_1}{p_2 g_{21} + \sigma^2})$ and $r_2 = w\log(1+\frac{p_2 g_2}{p_1 g_{12} + \sigma^2})$. As u is non-concave in p_1 and p_2, finding the global maximum is intractable. However, we can get some effective approaches by restricting our attention to some special regimes.

A. Circuit Power Dominated Regime

In this regime, circuit power dominates power consumption, i.e. $p_c \gg p_n$ for $n = 1, 2$. This is usually true for short-range communications as small transmit power is needed to compensate path loss. In this case, we have

$$u(p_1, p_2) \approx \frac{w}{p_c}\left(\log(1+\frac{p_1 g_1}{p_2 g_{21} + \sigma^2}) + \log(1+\frac{p_2 g_2}{p_1 g_{12} + \sigma^2})\right). \tag{8}$$

Hence, maximizing EE is equivalent to maximizing sum network capacity, which has been discussed in literature [6]. The optimal solution takes on the form of binary power control where each user either shuts down or transmits with full power. Whether two users transmit simultaneously or exclusively depends on interference strength.

B. Transmit Power Dominated Regime

When the circuit power is negligible, e.g. in extremely long distance communications where transmit power should be strong enough to mitigate large path loss,

$$u(p_1, p_2) \approx \frac{w\log(1+\frac{p_1 g_1}{p_2 g_{21} + \sigma^2})}{p_1} + \frac{w\log(1+\frac{p_2 g_2}{p_1 g_{12} + \sigma^2})}{p_2}. \tag{9}$$

$u(p_1, p_2)$ is strictly decreasing with both p_1 and p_2. Hence, the optimal solution is to allocate as low power as possible. However, the above conclusion holds only when the circuit power is negligible. When the transmit power is comparable to the circuit power, other approaches are needed to determine the optimal power.

C. Noise Dominated Regime

Now we look at the problem from a different perspective. When noise is much stronger than interference, we have

$$u(p_1, p_2) \approx \frac{w\log(1+\frac{p_1 g_1}{\sigma^2})}{p_1 + p_c} + \frac{w\log(1+\frac{p_2 g_2}{\sigma^2})}{p_2 + p_c}. \tag{10}$$

Hence, the problem is decoupled and the sum network EE is maximized when each user selects power to maximize their own EE, which is given in [2], [3].

D. Interference Dominated Regime

In the interference dominated regime, interference is much stronger than noise, i.e. $p_1 g_{12} \gg \sigma^2$ and $p_2 g_{21} \gg \sigma^2$ for any feasible p_1 and p_2 that support reliable transmission. To be specific, we require that $p_1 g_{12} \gg \sigma^2$ and $p_2 g_{21} \gg \sigma^2$ are significant enough that the *interference-to-noise ratio* (INR) and SINR of each user satisfies

$$INR > 1 + SINR. \tag{11}$$

Note that Equation (11) does exists when the interference is strong enough since INR increases with interference power while SINR decreases with it. The interference dominated regime exists when different transmissions are close to each other, e.g. closely coupled. Hence,

$$u(p_1, p_2) \approx \frac{w\log(1+\frac{p_1 g_1}{p_2 g_{21}})}{p_1 + p_c} + \frac{w\log(1+\frac{p_2 g_2}{p_1 g_{12}})}{p_2 + p_c}. \tag{12}$$

We can show that $u(p_1, p_2)$ is maximized by an ON-OFF approach, i.e. letting the user with higher channel gain to transmit with energy-efficient power selection and shutting down the other.

IV. Noncooperative Energy-Efficient Communications

The above section discusses energy-efficient power optimization with ideal cooperation in a two-user network. Extension to special regimes for a multi-user network is straightforward and omitted. However, in general, it is difficult to determine the globally optimal power allocation due to the nonconcavity of sum energy-efficiency functions. Even if the globally optimal solution can be found, it is still impractical since it requires complete network knowledge, including interference channel gains. In this section, we consider a more practical case and assume no cooperation among users.

A. A Noncooperative Game

We model the power control to be a noncooperative game in game theory. In a noncooperative game, each user optimizes power allocation to maximize its energy efficiency. Consider the power allocation of User n and denote the power vectors of other users to be vector

$$\mathbf{p}_{-n} = (\mathbf{p}_1^T, \mathbf{p}_2^T, \cdots, \mathbf{p}_{n-1}^T, \mathbf{p}_{n+1}^T, \cdots, \mathbf{p}_N^T)^T. \tag{13}$$

Given $\mathbf{p}_{-n}$, the best response of the power allocation of User n is

$$\mathbf{p}_n^o = f_n(\mathbf{p}_{-n}) = \arg\max_{\mathbf{p}_n} u_n(\mathbf{p}_n, \mathbf{p}_{-n}), \tag{14}$$

where u_n is given by (5) and is a function of both $\mathbf{p}_n$ and $\mathbf{p}_{-n}$. $f_n(\mathbf{p}_{-n})$ is called the best response function of User n. The existence and uniqueness of $\mathbf{p}_n^o$, i.e. the best response, is assured by Theorem I in our previous work [3].

Note that noncooperative power control is not efficient in terms of SE optimization since users tend to act selfishly by increasing their transmit power beyond what is reasonable. Hence, pricing mechanisms are introduced to regulate the aggressive power transmission by individuals to produce more socially beneficial outcome towards improving sum throughput of all users. Different from SE optimal power control, energy-efficient power optimization desires a power setting that is greedy in EE but chary of power. Furthermore, Problem (14) is equivalent to

$$\mathbf{p}_n^o = \arg\max_{\mathbf{p}_n} \left(\log(r_n) - \log(p_n + p_c)\right), \tag{15}$$

which implies that energy-efficient power control can be regarded as a variation of traditional spectral-efficient one with power pricing. Since this power-conservative expression is socially favorable in interference-limited scenarios, energy-efficient power control is desirable to reduce interference and improve throughput in a noncooperative setting.

Equilibrium is the condition of a network in which competing influences are balanced assuming invariant channel conditions. Its properties are important to network performance. Hence, we characterize the equilibrium of noncooperative energy-efficient power optimization in the following three sections. In a noncooperative game, a set of strategies is said to be at Nash equilibrium, referred as equilibrium in the following, if no user can gain individually by unilaterally altering its own strategy. Denote the equilibrium as

$$\mathbf{p}^* = (\mathbf{p}_1^*, \mathbf{p}_2^*, \cdots, \mathbf{p}_N^*). \tag{16}$$

Nash equilibrium can be described by the following definition.

Definition 1. *In an energy-efficient noncooperative game, an equilibrium is a set of power allocation that no user can unilaterally improve its energy efficiency by choosing a different set of power allocation, i.e.*

$$\mathbf{p}^* = f(\mathbf{p}^*) = (f_1(\mathbf{p}_{-1}^*), f_2(\mathbf{p}_{-2}^*), \cdots, f_N(\mathbf{p}_{-N}^*)), \tag{17}$$

where $f(\mathbf{p})$ is the network response function.

To facilitate our discussion, we first introduce the concept of quasiconcavity.

Definition 2. *A function z, which maps from a convex set of real n-dimensional vectors, $\mathcal{D}$, to a real number, is called strictly quasiconcave if for any $\mathbf{x}_1, \mathbf{x}_2 \in \mathcal{D}$ and $\mathbf{x}_1 \neq \mathbf{x}_2$,*

$$z(\lambda\mathbf{x}_1 + (1-\lambda)\mathbf{x}_2) > \min\{z(\mathbf{x}_1), z(\mathbf{x}_2)\}, \tag{18}$$

for any $0 < \lambda < 1$.

$u_n(\mathbf{p}_n, \mathbf{p}_{-n})$ is strictly quasiconcave in $\mathbf{p}_n$[‡]. The existence of equilibrium $\mathbf{p}^*$ is given by Theorem 1.

Theorem 1 (Existence)**.** *There exists at least one equilibrium $\mathbf{p}^*$ in the noncooperative energy-efficient power optimization game defined by (14). A set of power allocations of all users, $\mathbf{p}^* = (\mathbf{p}_1^*, \mathbf{p}_2^*, \cdots, \mathbf{p}_N^*)$, is an equilibrium if and only if it satisfies that, for any Subchannel i of any User n,*

(i) if $\frac{\sum_{j\neq i} r_n^{(j)*}}{p_c+\sum_{j\neq i} p_n^{(j)*}} \leq R'(0)\gamma_n^{(i)*}$, $\left.\frac{\partial u_n(\mathbf{p}_n, \mathbf{p}_{-n}^*)}{\partial p_n^{(i)}}\right|_{\mathbf{p}_n=\mathbf{p}_n^*} = 0$, i.e. $R'(\gamma_n^{(i)*}p_n^{(i)*})\gamma_n^{(i)*} = u(\mathbf{p}_n^*, \mathbf{p}_{-n}^*)$;

(ii) otherwise, $p_n^{(i)*} = 0$,

where $\gamma_n^{(i)*} = \frac{g_{nn}^{(i)}}{\sum_{j=1,j\neq n}^N p_j^{(i)*} g_{jn}^{(i)} + \sigma^2}$.

First, we consider a special case when there is a single subchannel in a network.

Proposition 1. *When there is only one subchannel, the power allocations, i.e. the response functions, of all users satisfy*

- *Concavity: $f_n(\mathbf{p}_{-n})$ is strictly concave in $\mathbf{p}_{-n}$;*
- *Positivity: $f_n(\mathbf{p}_{-n}) > 0$;*
- *Monotonicity: If $\mathbf{p}_{-n} \succ \mathbf{q}_{-n}$, $f_n(\mathbf{p}_{-n}) > f_n(\mathbf{q}_{-n})$;*
- *Scalability: For all $\alpha > 1$, $\alpha f_n(\mathbf{p}_{-n}) > f_n(\alpha\mathbf{p}_{-n})$,*

where $\succ$ denotes vector inequality and each element of the vector satisfies the inequality.

Note that the monotonicity indicates that increasing interference results in increasing transmit power while the scalability indicates that variation of transmit power is always smaller than that of the interference power. These assure the convergence to a unique equilibrium.

The properties in Proposition 1 can be extended to networks with multiple subchannels where all subchannels experience the same channel gain, i.e. flat-fading channels. This can be done by defining $f_n(\mathbf{p}_{-n})$ to be the optimal total transmit power on all subchannels. Now we have the following result.

Theorem 2 (Uniqueness)**.** *When the channel experiences flat fading, there exists one and only one equilibrium $\mathbf{p}^*$ in the noncooperative energy-efficient power optimization game defined by (14).*

When there are multiple subchannels which experience frequency-selective fading, whether there is a unique equilibrium depends on channel conditions. Consider a network with two users as an example. Let $p_c = 1, w = 1, \sigma^2 = 1, g_{11}^{(1)} = g_{11}^{(2)} = g_{22}^{(1)} = g_{22}^{(2)} = 1, g_{12}^{(1)} = g_{21}^{(1)} = 1e^{-10}, g_{12}^{(2)} = g_{21}^{(2)} = 1e^{10}$. We can show that one of the equilibrium has the form $\mathbf{p}_1^* = [p_a\ p_b]$ and $\mathbf{p}_2^* = [p_c\ 0]$, where p_a, p_b, and p_c are positive. Due to the symmetry of network conditions, $\mathbf{p}_1 = [p_c\ 0]$ and $\mathbf{p}_2 = [p_a\ p_b]$ also form an equilibrium. Hence, the network has at least two equilibria. When there are more users and subchannels, more equilibria will exist in general. However, we show that when the interfering channels satisfy a certain condition, there will be a unique equilibrium.

Denote the Jacobian matrix of $\tilde{F}_n$ at $\mathbf{I}_n$ to be $\frac{\partial \tilde{F}_n}{\partial \mathbf{I}_n}$ and the Jacobian matrix of $\mathbf{I}_n$ at $\mathbf{p}_{-n}$ to be $\frac{\partial \mathbf{I}_n}{\partial \mathbf{p}_{-n}}$. Denote $||A||$ to be the Frobenius norm of matrix $A = (a_{ij})$, i.e. $||A|| = \sqrt{\sum_{i,j} a_{ij}^2}$. Readily, we have the following sufficient condition that assures a unique equilibrium.

[‡]All proofs are omitted. Users are referred to the journal version for more details

Theorem 3 (Uniqueness)**.** *In frequency selective channels, the noncooperative energy-efficient power optimization game defined by (14) has a unique equilibrium if for any User* n*,* $||f_n(\mathbf{p}_{-n}) - f_n(\check{\mathbf{p}}_{-n})|| < ||\mathbf{p}_{-n} - \check{\mathbf{p}}_{-n}||$ *for any different* $\mathbf{p}_{-n}$ *and* $\check{\mathbf{p}}_{-n}$ *or* $\left|\left|\frac{\partial \mathbf{I}_n}{\partial \mathbf{p}_{-n}}\right|\right| < \frac{1}{\sup_{\mathbf{I}_n} \left|\left|\frac{\partial f_n}{\partial \mathbf{I}_n}\right|\right|}$.

Extension of the above theorem to general noncooperative multichannel power control is straightforward. Note the generalization of assuring a unique equilibrium can be applied to different kinds of distributed MIMO and OFDM systems.

The above theorem gives sufficient conditions of uniqueness that may not be necessary ones. For example for a single-channel network, due to the strict concavity of $f_n(\mathbf{p}_{-n})$, $\sup_{I_n} \left|\left|\frac{\partial f_n}{\partial I_n}\right|\right| = \left.\frac{\partial f_n}{\partial I_n}\right|_{I_n=0}$. However, for all interference channel gains, there is always a unique equilibrium, as shown in Theorem 2.

B. SE and EE Tradeoff without Cooperation

In this section, we investigate the tradeoff between noncooperative energy-efficient power optimization and noncooperative spectral-efficient power control schemes. Here, no peak power constraint is assumed to investigate performance limit. Consider a symmetric single-channel network to simplify analysis and to get insights. There are N users, all experiencing the same channel power gain g. All interference channels have the same power gain $\widetilde{g}$. Define network coupling factor to be

$$\alpha = \frac{\widetilde{g}}{g}. \tag{19}$$

Consider the equilibrium, which is unique according to Theorem 2. Due to the assumption of network symmetry, all users transmit with the same power in the equilibrium. Denote the transmit power of all users to be p.

The overall network EE is

$$u(p) = \frac{Nw \log\left(1 + \frac{p}{(N-1)\alpha p + \frac{\sigma^2}{g}}\right)}{p + p_c}, \tag{20}$$

and the network SE is

$$r(p) = N \log\left(1 + \frac{p}{(N-1)\alpha p + \frac{\sigma^2}{g}}\right). \tag{21}$$

With noncooperative spectral-efficient power control, every user allocates power to selfishly maximize its SE. Without power limit, the transmit power tends to infinity in the equilibrium. Besides, we can see that $r(p)$ is strictly increasing in p. Hence, the maximum network SE is obtained in the equilibrium and the upperbound is

$$r_{SE} = \lim_{p\to\infty} r(p) = N \log(1 + \frac{1}{(N-1)\alpha}) \tag{22}$$

with the corresponding EE $u_{SE} = \lim_{p\to\infty} u(p) = 0$, which is completely energy inefficient and noncooperative SE optimal power control is not desired for energy efficiency.

With noncooperative energy-efficient power optimization, the network energy efficiency at the equilibrium is $u_{EE} = u(p^*)$ with the corresponding SE $r_{EE} = r(p^*)$. Hence, the SE penalty of energy-efficient power optimization is

$$r_{tr} = r_{SE} - r_{EE} = N \log(1 + \frac{1}{(N-1)\alpha}) - r(p^*). \tag{23}$$

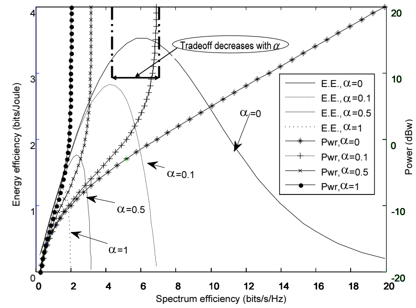


Fig. 1: Tradeoff of EE and SE with different interfering scenarios ($p_c = 1, g = 1, \sigma^2 = 0.01, N = 2$).

In an interference-free scenario, i.e. $N = 1$ or $\alpha = 0$, the penalty is infinite. Otherwise, whenever interference exists, it is bounded.

To further understand the tradeoff, Figure 1 illustrates a case when two users transmit with the same power and interfere with each other. Curves with markers draw the relationship between transmit power and SE when the network has different couplings while those without markers draw the corresponding energy efficiency. When $\alpha = 0$, arbitrary SE can be obtained by choosing enough transmit power. When $\alpha > 0$, regions beyond the SE upperbound is not achievable. Furthermore, EE is much more sensitive to power selection than SE. In interference-limited scenarios, increasing transmit power beyond the optimal power for EE has little SE improvement but significantly hurts EE. Furthermore, power optimization to achieve the highest energy efficiency will also have reduced SE tradeoff with the increase of α. We also show that the equilibrium power decreases with either user number or α and automatically alleviates network interference.

C. Implementation

In (14), the best response of User n depends on the transmit power vectors of all other users, $\mathbf{p}_{-n}$, which can not be obtained in a noncooperative setting. Instead, we observe that $\mathbf{p}_{-n}$ affects the best response in the form of interference, which thus contains sufficient information of $\mathbf{p}_{-n}$ to determine the best response and can be acquired locally. Hence, we let each user measure interferences on all subchannels to determine the power optimization. We introduce a *temporal iterative binary search* (TIBS) algorithm to track channel temporal variation and search for the optimal power allocation with reduced complexity. TIBS searches a better power allocation along the gradient at each time slot and enable iterative search along time. The power at t is updated by

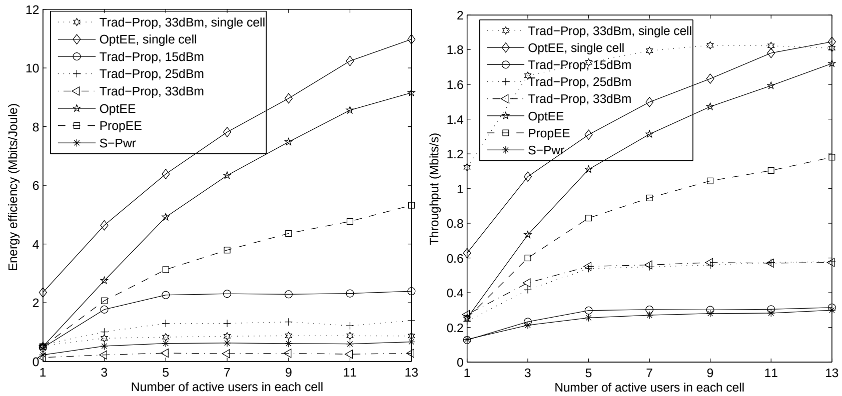
$$\mathbf{p}_n[t] = \mathbf{p}_n[t-1] + \mu(\nabla \widehat{u}_{n[t]})_{\mathbf{p}_n[t-1]}, \tag{24}$$

where $\widehat{u}_{n[t]}$ is the EE calculated based on measured interference; $(\nabla \widehat{u}_{n[t]})_{\mathbf{p}_n[t-1]}$ is the gradient of $\widehat{u}_{n[t]}$ at $\mathbf{p}_n[t-1]$; and μ is a small step size. Small step size leads to slow convergence and channel tracking capability. Denote

$$g(\mu) = \widehat{u}_{n[t]}(\mathbf{p}_n[t-1] + \mu(\nabla \widehat{u}_{n[t]})_{\mathbf{p}_n[t-1]}). \tag{25}$$

$g(\mu)$ is also strictly quasi-concave in μ and binary search can be used for rapid location of the optimal step size μ^* [3]. TIBS is summarized in the following algorithm.

Algorithm *Temporal Iterative Binary Search (TIBS)*
($*$ noncooperative energy-efficient power optimization $*$)
Input: $\mathbf{p}[t-1]$, $\mathbf{I}[t-1]$



(a) Energy efficiency (b) Throughput

Fig. 2: Performance comparison of different schemes

TABLE I: System Parameters

Carrier frequency	1.5 GHz
Number of subchannels	96
Subchannel bandwidth	10 kHz
Target BER	10^{-3}
Thermal noise power, N_o	-141 dBW/MHz
Circuit power, P_C	100 mW
Maximum transmit power	33 dBm
Propagation model	Okumura-Hata model
Shadowing	Log-normal
Fading	Rayleigh flat fading
Modulation	Uncoded M-QAM

Output: $\mathbf{p}[t]$

1. use *Gradient Assisted Binary Search*([3]) to find the optimal step size μ^*;
2. $\mathbf{p}[t] = \mathbf{p}[t-1] + \mu^*(\nabla\widehat{u}[t])_{\mathbf{p}[t-1]}$,
3. **return** $\mathbf{p}[t]$

V. Simulation Results

In this section we present simulation results for an interference-limited Uplink OFDMA cellular network with reuse one. The network consists of seven hexagonal cells and the center cell is surrounded by the other six. Users are uniformly dropped into each cell at each simulation trial. The system parameters are listed in Tables I and II. We also implement a traditional soft power control scheme [7]. In this scheme, parameters are selected to find the best tradeoff between the average system SE and the throughput performance of cell-edge users. Figure 2 compares the average sum network EE and the corresponding throughput performance respectively. For fixed-power transmission, the transmit powers are shown in the legend. To see performance loss due to interference, the energy-efficient scheduler without fairness and the traditional proportional scheduler with the maximum transmit power is also simulated in a single cell network. We can see that transmitting with the highest power brings the highest interference and causes significant throughput loss for the traditional scheduler. In contrast, energy-efficient power control effectively reduces network interference and has much less throughput loss. While our previous results in [2] show that EE and throughput efficiency do not necessarily agree for an interference-free single cell scenario, the situation is different for a multi-cell interference-limited network. Here energy-efficient schemes optimize both throughput and energy utilization and exhibit an improved SE tradeoff. Further results show that EE schemes not only improve the sum energy efficiency and throughput, but also uniformly improve the performance of all users in the cell.

TABLE II: Scheduling and Power Control

Legend	Scheduler	Power control
OptEE	Energy-efficient scheduler w/o fairness	TIBS
PropEE	Energy-efficient scheduler w/ proportional fairness	TIBS
Trad-Prop	Traditional proportional fair	Fixed power
S-Pwr	Traditional proportional fair	Traditional power control

VI. Conclusion

We investigate energy-efficient power optimization for interference-limited communications. To gain insight into this problem, we first study a two-user network with ideal user cooperation and get effective approaches for specific regimes. Then we develop a non-cooperative power allocation scheme. Simulation results show that energy-efficient power optimization improves not only EE but also SE due to the conservative nature of power allocation, which reduces other-cell interference to improve the overall network throughput.

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