Self-Optimization in Mobile Cellular Networks: Power Control and User Association

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***Abstract*—In this work, we develop mathematical and algorithmic tools for the self-optimization of mobile cellular networks. Scalable algorithms which are based on local measurements and do not require heavy coordination among the wireless devices are proposed. We focus on the optimization of transmit power and of user association. The method is applicable to both joint and separate optimizations. The global utility minimized is linked to potential delay fairness. The distributed algorithm adaptively updates the system parameters and achieves global optimality by measuring SINR and interference. It is built on Gibbs' sampler and offers a unified framework that can be easily reused for different purposes. Simulation results demonstrate the effectiveness of the algorithm.**

I. Introduction

In 4G and future cellular mobile radio systems, network self-organization and self-optimization are among the key targets [1]. Autonomic management is desirable to relax the heavy requirement of human efforts in conventional network planning and optimization tasks [2]. For example, base stations (BSs) should automatically adjust their operational parameters to achieve the best network performance and adapt to system dynamics such as traffic and environment changes. In practice [3], self organization and optimization will help to improve the overall quality-of-service (QoS) and also reduce the system capital and operational expenditure (CAPEX/OPEX).

System-wide radio resource optimization is however usually quite challenging. In today's broadband wireless networks, traditional schemes [4]–[6] designed for voice-centric service may not be effective for overall network throughput maximization or traffic delay minimization. It requires the solution of a multi-cell and multi-link optimization in which different transmitters or links cooperate for the benefit of overall improvement and where fairness issues should be addressed [7]–[9].

It is well known that power control, user association and channel allocation are essential issues in many wireless systems including mobile cellular and wireless ad hoc networks [10], [11]. However, optimizing these parameters is often difficult. For example, the optimization of transmission power for system throughput maximization over multiple interfering links is in general non-convex [7]. Therefore, it is hard to have an efficient optimization algorithm that works in a distributed manner and also ensures global optimality. The only known power control algorithm that can guarantee strict throughput maximization in general SINR regime is reported in [12]. It is built on multiplicative linear fractional programming for optimization problems expressible as a difference of two convex functions. However, this algorithm requires a centralized control and is only efficient for problem instances of small scale due to the computation complexity.

In this paper, we focus on the development of distributed self-optimization tools for cellular networks based on Gibbs' sampler (see, e.g., [13, pp. 285–290]) and the methodology developed in [10] for IEEE 802.11 networks. The aim is to design scalable algorithms which achieve global optimality but only require local information exchange and operations. To the best of our knowledge, this is the first time this technique is applied to power control and user association in reuse 1 cellular networks. By decisions based on local measurements of interference, the algorithm drives the network into the optimal configuration.

The rest of the paper is organized as follows. Section II describes the system model and problem formulation. Section III presents the proposed power control algorithm. Section IV generalizes the result to user association and joint optimization. Section V contains numerical studies. Finally, Section VI gives the conclusion.

II. System Model and Formulation

We consider a reuse 1 cellular radio system with a set of base stations $\mathcal{B}$, which serve a population of users denoted by set $\mathcal{U}$. For each user, we assume there is a pair of orthogonal channels for uplink and downlink communications respectively. Since there is no interference between the uplink and downlink, for simplicity we only consider the downlink in the present paper. However, the discussion can be generalized to the uplink as well.

To begin with, we consider that each user $u \in \mathcal{U}$ is associated with the closest BS $b_u \in \mathcal{B}$ that is the element $b \in \mathcal{B}$ such that the signal attenuation from b to u, denoted by $l(b, u)$, is the smallest. Note that this assumption will be relaxed in the sequel when our scheme will be generalized to user association optimization.

Denote by P_u the power used by b_u to transmit data destined to u; the SINR (signal-to-interference-plus-noise ratio) at u is expressible as:

$$\text{SINR}_u = \frac{P_u \cdot l(b_u, u)}{N_u + \sum_{v \in \mathcal{U}, v \neq u} \alpha(v, u) \cdot P_v \cdot l(b_v, u)} , \qquad (1)$$

where N_u denotes the receiver noise at u, and $\alpha(v,u)$ represents the orthogonality factor on the transmission destined to $v \in \mathcal{U}$. Note that $0 \leq \alpha \leq 1$.

A. Cost Function

For a balance between network throughput enhancement and bandwidth fair sharing among users, we use the notion of minimal *potential delay fairness* proposed in [14]. This solution for bandwidth (resource) sharing is intermediate between max-min and proportional fairness. Instead of maximizing the sum of throughputs, i.e., $\sum r_u$, which often leads to very low throughput for some users, it minimizes the sum of the inverse of throughput, i.e., $\sum(1/r_u)$, or equivalently the total delay to send an information unit to *all* users, which penalizes very low throughputs.

In other words, a bandwidth allocation that minimizes potential delay is one that minimizes the following cost function:

$$C = \sum_{u \in \mathcal{U}} \frac{1}{r_u} \ , \tag{2}$$

which is the network's aggregate transmission delay.

Under the additive white Gaussian noise (AWGN) model, the achievable data rate in bits/s/Hz at u is given by

$$r_u = K \log(1 + \text{SINR}_u) \ , \tag{3}$$

where K is a constant which depends on the width of the frequency band. Below, we actually minimize the following cost function:

$$\mathcal{E} = \sum_{u \in \mathcal{U}} \frac{1}{e^{\frac{r_u}{K}} - 1} = \sum_{u \in \mathcal{U}} \frac{1}{\text{SINR}_u} \ , \tag{4}$$

which will be the global *energy* of the Gibbs sampler. The reason for this is primarily mathematical convenience (see below). Note that if one operates in a low SINR regime such that the achievable data rate of a user is proportional to its SINR, e.g., $r_u = K\text{SINR}_u$, then minimizing potential delay C of (2) is equivalent to minimizing $\mathcal{E}$ of (4).

One can see that (2) and (4) have quite similar characteristics. Notice that $1/(e^{\frac{r_u}{K}} - 1)$ increases more significantly than $1/r_u$ and yields a more substantial rise in the cost function, when r_u is low.

Therefore, minimizing $\mathcal{E}$ rather than C penalizes low throughputs more and favors a higher level of fairness among all the users.

B. Gibbs Sampler Formulation

Substituting (3) into (4), the global energy can be written as:

$$\mathcal{E} = \sum_{u \in \mathcal{U}} \frac{N_u}{P_u \cdot l(b_u,u)} + \sum_{u,v \in \mathcal{U},\, v \neq u} \frac{\alpha(v,u) P_v \cdot l(b_v,u)}{P_u \cdot l(b_u,u)}$$

or equivalently as:

$$\begin{aligned} \mathcal{E} \ &= \ \sum_{u \in \mathcal{U}} \frac{N_u}{P_u \cdot l(b_u,u)} + \\ &\sum_{\{u,v\} \subseteq \mathcal{U}} \left(\frac{\alpha(v,u) P_v \cdot l(b_v,u)}{P_u \cdot l(b_u,u)} + \frac{\alpha(u,v) P_u \cdot l(b_u,v)}{P_v \cdot l(b_v,v)} \right) . \end{aligned} \tag{5}$$

We will say that the orthogonality factor is symmetrical if $\alpha(v,u) = \alpha(u,v)$, for all $u,v \in \mathcal{U}$.

For all subsets $\mathcal{V} \subseteq \mathcal{U}$, let $|\mathcal{V}|$ denotes the cardinality of $\mathcal{V}$. We have

$$\mathcal{E} = \sum_{\mathcal{V} \subseteq \mathcal{U}} V(\mathcal{V}) \ , \tag{6}$$

with $V(.)$ the following *potential* function:

$$\begin{cases} V(\mathcal{V}) &= \dfrac{N_u}{P_u \cdot l(b_u,u)} \qquad \text{if } \ \mathcal{V} = \{u\}, \\ V(\mathcal{V}) &= \dfrac{\alpha(v,u) P_v \cdot l(b_v,u)}{P_u \cdot l(b_u,u)} + \dfrac{\alpha(u,v) P_u \cdot l(b_u,v)}{P_v \cdot l(b_v,v)} \\ & \qquad \text{if } \ \mathcal{V} = \{u,v\}, \\ V(\mathcal{V}) &= 0 \qquad \text{if } \ |\mathcal{V}| \geq 3. \end{cases}$$

The local energy $\mathcal{E}_u$ of user u is defined as:

$$\mathcal{E}_u = \sum \{V(\mathcal{V}) | u \in \mathcal{V} \ , \mathcal{V} \subseteq \mathcal{U}\} \ . \tag{7}$$

Using the definition of $V(\mathcal{V})$, we have:

$$\mathcal{E}_u = \underbrace{\frac{N_u}{P_u l(b_u,u)} + \sum_{v \neq u} \frac{\alpha(v,u) P_v l(b_v,u)}{P_u l(b_u,u)}}_{=1/(\text{SINR}_u)} + \sum_{v \neq u} \frac{\alpha(u,v) P_u l(b_u,v)}{P_v l(b_v,v)} \ , \tag{8}$$

which can be seen as a function of P where $P = P_u$, and can be written in the following form:

$$\mathcal{E}_u(P) = \frac{A_u}{P} + B_u P \ , \tag{9}$$

where

$$A_u \ \triangleq \ \frac{N_u}{l(b_u,u)} + \sum_{v \neq u} \frac{\alpha(v,u) P_v \cdot l(b_v,u)}{l(b_u,u)}$$

and

$$B_u \ \triangleq \ \sum_{v \neq u} \frac{\alpha(u,v) l(b_u,v)}{P_v \cdot l(b_v,v)}.$$

Notice that the first term $A_u P^{-1}$ in (9) can be seen as the "selfish" part of the energy function which is small if the SINR of user u is large, whereas the second term $B_u P$ is the "altruistic" part of the energy, which is small if the power of interference incurred by all the other users, i.e., $v \neq u$, because of P is small compared to the power received from their own BSs.

Remark 1: In (8), when multiplying all the powers by the same constant, all the terms are unchanged except the noise-to-signal ratio which will be decreased. Thus, the optimal values will favor large powers. In what follows, we will assume bounded transmission powers. This observation also implies that at the optimum, at least one of the powers will be at its maximal value (see, e.g., [8]).

Remark 2: This global energy derives from the above potential function is hence amenable to a distributed optimization. This explains the choice made in (4).

III. Power Control

We now describe a distributed algorithm for power control (PC), which aims at minimizing the *global* energy/cost given by (6). We first describe very roughly what this algorithm does and achieves:

- Through measurements and information exchange between neighboring BSs[1], the coefficients A_u and B_u of the local energy (9) are evaluated;
- Each BS separately triggers a transition (i.e., a power adjustment applied to one of its users picked at random, say u) using a local random timer; this transition, which is only based on the evaluation of the coefficients of the local energy $\mathcal{E}_u$, consists in selecting a transmission power with low local energy with high probability. The precise definition of the transition, which depends on a parameter T called the temperature, is given below.
- The dynamics based on these local transitions, called the Gibbs sampler, lead to a steady state which is the *Gibbs distribution* associated with this global energy and temperature T, namely the following distribution on the power vectors:
$$\pi_T(P_u, u \in \mathcal{U}) = c \exp(-\mathcal{E}(P_u, u \in \mathcal{U})/T),$$
with c a normalizing constant.
- This distribution puts more mass on low energy (small cost) power configurations. When T goes to 0 in an appropriate way, the distribution $\pi_T(.)$ converges to a dirac mass at the power vector $(P_u, u \in \mathcal{U})$ with minimal cost if it is unique.

We now describe the algorithm in more precise terms.

A. Graph of the Gibbs Sampler

The Gibbs sampler operates on the graph defined below:

- The set of *nodes* of the graph is the set of users.
- Each node has a *state* which is its power (which is discretized).
- The set of *neighbors* of node u in this graph is the set of all users $v \neq u$ such that the power of the signal received from BS b_v at u is above a specific threshold, say θ (for practical consideration, we assume that it is the same for all).

B. Information Collection and Exchange

As aforementioned, the state transition (i.e., power control) is based on the coefficients of the local energy $\mathcal{E}_u$. So, the BS b_u needs to gather some information so as to determine the coefficients of $\mathcal{E}_u$. To do so, each user $v \in \mathcal{U}$ reports the following data to its BS b_v:

1) its SINR_v,
2) the power of its received signal, i.e., $\tilde{P}(b_v, v) \triangleq P_v \cdot l(b_v, v)$,[2] and
3) the power of the signal received from the other BSs, i.e. $\tilde{P}(b_u, v) \triangleq \alpha(u,v) P_u \cdot l(b_u, v)$.[3]

Let $\mathcal{U}_c$ denote the set of users of BS c. Using 2) and 3) Each BS c can determine the set

$$S_c = \{b, v \in \mathcal{U}_c \text{ s.t. } \tilde{P}(b,v) > \theta\} \ . \tag{10}$$

These values will be updated only if the geometry of the users or the condition of the wireless medium change. BS c then reports the following aggregate ratio $\{I_{b,c}(u)\}$ to each neighboring BS b:

$$\left\{ I_{b,c}(u) = \sum_{v \in S_c} \frac{\alpha(u,v) P_u \cdot l(b,v)}{P_v \cdot l(c,v)} \right\}_{u \in \mathcal{U}_b} . \tag{11}$$

Note that the above communication takes place between neighboring BSs b and c. So, there is no need to transmit this information on the wireless medium. The coefficient B_u can be deduced by BS b_u by summation of these aggregate ratios and division by P_u.

C. Evaluation of the Coefficients of Local Energy

From the collected information, each BS b_u is able to compute the parameters A_u and B_u that show up in the local energy $\mathcal{E}_u$ associated with each of its users.

Using 1), the BS b_u can determine A_u by computing P_u/SINR_u. The coefficient B_u can be computed from the ratios of $I_{b,c}(u)$ advertised by neighboring BSs, since (9) is expressible as:

$$B_u P_u = \sum_{v \in \mathcal{U}_b, v \neq u} \frac{\alpha(u,v) P_u}{P_v} + \sum_{c \neq b} \sum_{v \in \mathcal{U}_c} \frac{\alpha(u,v) P_u \cdot l(b,v)}{P_v \cdot l(c,v)} \ ,$$

where $b = b_u$, and b and c are implicit neighbors. We have

$$B_u = \sum_{v \in \mathcal{U}_b, v \neq u} \frac{\alpha(u,v)}{P_v} + \sum_{c \neq b} \frac{I_{b,c}(u)}{P_u}. \tag{12}$$

Note that in (12), for $v \in \mathcal{U}_b$, since $b_v = b_u$, both P_v and $\alpha(u,v)$ are known by the same BS.

D. Updtate Algorithm

The BS updates the powers using Algorithm 1 described below. For each user associated with this BS, we set a timer, t_u, that decreases linearly with time. Here, we consider discrete time in step of δ second(s) and simply set $\delta = 1$. This timer has an expiration time randomly generated according to a geometric distribution. When t_u expires, a *transition* occurs by which the power, P_u, for this user is updated. This update consists in selecting a new power P for user u according to the following probability distribution, given the state of the graph (namely given the other powers):

$$\pi_u(P) = \frac{e^{-\mathcal{E}_u(P)/T}}{\sum_{P \in \mathcal{P}} e^{-\mathcal{E}_u(P)/T}} \tag{13}$$

where $T > 0$ is the temperature and $\mathcal{P}$ the discrete set in which powers are selected. For practical reasons, power levels

[1]Two BSs, say b and c, are called *implicit neighbors* if at least one user associated with one BS receives the signal of the other BS above the threshold.

[2]Or, the attenuation from b_v to v, i.e., $l(b_v, v)$, as P_v is known at b_v.

[3]Or, $\alpha(u,v) l(b_u, v)$. Note that $\tilde{P}(b_u, v)$ refers to interference.

are discretized in such a way that $\mathcal{P} = \{0, P_\delta, 2P_\delta, \ldots, P_{\max}\}$, where $P_{\max}$ is the maximum transmission power and P_δ is the power step.

every δ *s* **do**
  foreach u *in the set* $\mathcal{U}_b$ **do**
    if $t_u \leq 0$ **then**
      measure SINR_u ;
      forall P *in* $\mathcal{P}$ **do**
        $\mathcal{E}_u(P) \leftarrow \frac{A_u}{P} +$
        $P\left(\sum_{v \in \mathcal{U}_b, v \neq u} \frac{\alpha(u,v)}{P_v} + \sum_{c \neq b} \frac{I_{b,c}(u)}{P_u}\right)$;
        $d_u(P) \leftarrow \exp\left(-\frac{\mathcal{E}_u(P)}{T}\right)$;
      end
      sample $P \in \mathcal{P}$ according to the probability law $\pi_u(P) \triangleq d_u(P)/(\sum_{P \in \mathcal{P}} d_u(P))$;
      sample $t_u \geq 0$ with distribution $\exp(1)$;
    else
      $t_u \leftarrow t_u - \delta$;
    end
  end
  forall c*: neighbors of* b **do**
    $I_{b,c}(u) \leftarrow \sum_{v \in \mathcal{U}_c} \frac{\alpha(u,v)P_u \cdot l(b,v)}{P_v \cdot l(c,v)}$;
    if $I_{b,c}(u)$ has changed, send its new value to b;
  end
end

Algorithm 1: power transition of base station b.

`test` x `test`

One can see in (13) that π_u favors *low* energies. As a result, in each state transition, the Gibbs sampler will sample a random variable $P \in \mathcal{P}$ having more likely a small $\mathcal{E}_u$.

E. Convergence

As previously mentioned, the setting of T will influence the limit distribution to be reached by the system. This parameter has to be chosen as a tradeoff between *strict* optimality of the limit distribution concentrating on state with lowest energy, and the convergence time. It is known that for a fixed environment (i.e., user population, signal attenuation), if one decreases T as $1/\log(t)$, where t is the time, this algorithm will drive the network to a state of minimal energy, starting from any arbitrary state (i.e., any initial power vector). We follow this and set $T = 1/\ln(1+t)$, where t starts from zero.

A proof of convergence of Algorithm 1 to the state of minimal $\mathcal{E}$ can be done similarly to that of [13, pp. 311-313] based on the notion of weak ergodicity of Markov chains and is thus omitted here. On the other hand, in Section V, the numerical study will illustrate the convergence property.

IV. User Association

We now relax the assumption that each user is associated with the closest BS. There are situations where such an assumption is sub-optimal. Fig. 1 gives an example of two BSs and two users in which both users u and v have the same closest BS, i.e., a. However, it is better to associate u with a, and v with b, rather than to associate both u and v with a, since the former association can lead to a lower overall interference and higher network capacity.

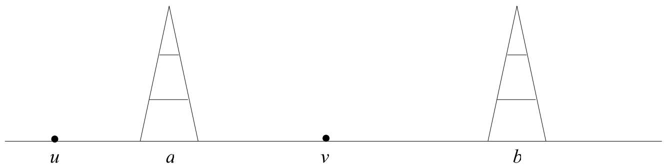

Fig. 1. The path loss from a to v is a little bit less than that from b to v. However, associating both u and v to a is sub-optimal.

In general, if one simply associates users with the closest BS or to that with the strongest received signal, it is possible that some BSs have many users while others have only a few. The resulting overload will lead to an overall performance degradation and user association (UA) optimization should hence be considered.

A. Joint Optimization

In the following, we generalize the previous Gibbs sampler to a joint optimization of UA and PC for driving the network to a state of minimal energy. The setting is the same as the above but now, the *state* of each node is a pair of (BS, power). To be practical, the set of candidate BSs of a user could be its k neighboring BSs (e.g., k may equal to 2 or 3) from which the power of signal received is above a certain threshold. The local energy now reads:

$$\begin{aligned}\mathcal{E}_u(b,P) &= \frac{N_u}{P \cdot l(b,u)} + \sum_{v \neq u} \frac{\alpha(v,u)P_v \cdot l(b_v,u)}{P \cdot l(b,u)} + \\ &\qquad \sum_{v \neq u} \frac{\alpha(u,v)P \cdot l(b,v)}{P_v \cdot l(b_v,v)} \\ &= \frac{\hat{A}_u(b)}{P} + \hat{B}_u(b)P \ , \end{aligned} \tag{14}$$

where

$$\hat{A}_u(b) \triangleq \frac{N_u}{l(b,u)} + \sum_{v \neq u} \frac{\alpha(v,u)P_v \cdot l(b_v,u)}{l(b,u)}$$

and

$$\hat{B}_u(b) \triangleq \sum_{v \neq u} \frac{\alpha(u,v)l(b,v)}{P_v \cdot l(b_v,v)}.$$

The above setting (14) is hence similar to that of (9). The same algorithm can be used with the following simple modification: sample the random variables on the set of pairs (b,P) according to the probability $\pi_u(b,P)$ that is proportional to $\exp(-\mathcal{E}_u(b,P)/T)$.

Note that to determine $\mathcal{E}_u(b,P)$ for the joint optimization, the information to be collected and feedback should include

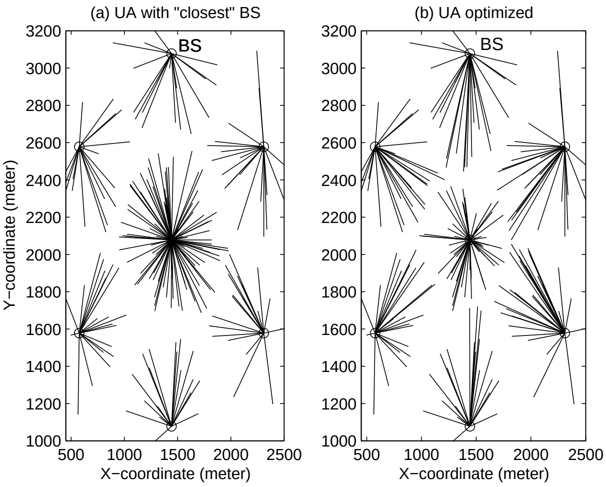

Fig. 2. User delay before and after optimization: (a) mean = 5.7358 μs/bit, s.d. = 2.2001 μs/bit, and (b) mean = 5.4439 μs/bit, s.d. = 2.0662 μs/bit.

the signal and interference measurements related to the considered BS candidates. The information exchange required will increase linearly with the average number of neighboring BSs. However, the operation and procedure are similar to those for determining (9).

B. User Association Only

A simplification of (14) is possible if one considers user association optimization without power control (e.g., the power vector is simply fixed). The local energy now reads:

$$\mathcal{E}_u(b) = \frac{N_u}{P_u \cdot l(b,u)} + \sum_{v \neq u} \frac{\alpha(v,u) P_v \cdot l(b_v,u)}{P_u \cdot l(b,u)} + \sum_{v \neq u} \frac{\alpha(u,v) P_u \cdot l(b,v)}{P_v \cdot l(b_v,v)} \quad (15)$$

which is a function of b, instead of (b, P). Consequently, we sample a random variable on the set of BS candidates according to the probability distribution $\pi_u(b)$ which is proportional to $\exp(-\mathcal{E}_u(b)/T)$.

Fig. 2 shows a topology of wireless hot spot in which users are relatively concentrated in the center of the geographical area. There are totally 210 users. 3GPP-3GPP2 spatial channel model [1, "C802.20-07-02.doc"] is employed. For demonstration, we simply set $P_u = 1$ W, $\alpha(u,v) = 0.1$, and channel bandwidth equal to 1 MHz, for all. By default, users are associated with their closest BS, as shown in Fig. 2(a). Clearly, the BS in the center has many users and will be overloaded. However, the other BSs have only a few users. The resulting load is unbalanced. We conduct UA optimization. As shown in Fig. 2(b), the new association is more even and has a better load balance, which leads to an improvement in the overall delay performance.

V. Numerical Studies

Based on the system model described in Section II, we employ the 3GPP-3GPP2 spatial channel model [1] for simulations. The urban micro-cellular system with hexagonal cell layout is adopted. BS-to-BS distance is set to 1 km, while users are assumed to be uniformly distributed in the geographic area, except that BS-to-user distance should exceed 20 meters as required by the model. The maximum transmission power $P_{\max}$ is set to 1 W, for all u. Distance dependent path loss is given by:

$$l^{(\mathrm{dB})}(d) = -(30.18 + 26\log_{10}(d) + X_\sigma^{(\mathrm{dB})}) \ , \quad (16)$$

where d is the transmitter-receiver distance and X_σ represents log-normal shadowing with zero mean and standard deviation 4 dB. With operating temperature 290 Kelvin and bandwidth 1 MHz, the thermal noise N_u is equal to 4.0039×10^{-15} W, for all u.

The considered system has 16 BSs and a total of 160 users. It consists of a cellular network with frequency reuse factor 1 and ten orthogonal channels for the downlink. As in [15], we consider co-channel and adjacent-channel orthogonality factors, denoted by (α_a, α_c), equal to (0.1, 0.5) and (0.1, 0.9) in two separate sets of simulations, respectively. Besides, given $P_{\max} = 1$ W, we assume that power step is $P_\delta = 1$ mW. In (10), the threshold θ for determining the implicit neighbor set is set to 20 dB above N_u, so that θ equals to -93.98 dBm.

We compare our solution to some reference scenario where users associate with their closest BS and where each transmission is conducted at $P_{\max}$. In the simulation of our solution, we only consider the scheme with separate optimizations: we first conduct UA optimization which aims at achieving user/load balancing and then conduct PC. Note that the formulation in (14) allows a joint optimization (see [16] for more on the matter in the CSMA/CA context).

Fig. 3 shows the evolution of global energy $\mathcal{E}$ during the power control phase in two randomly generated network topologies. We allow the algorithm to have a long run in the simulation. It is observed that $\mathcal{E}$ converges to its minimum quite fast. It takes about 30 iterations in both systems (i) and (ii). The evolution of algorithm in the UA optimization phase has a similar convergence speed. To avoid redundancy, we do not plot them here.

Fig. 4 shows the empirical cumulative distribution of long-term (averaged over 100 time iterations) transmission delay of users after UA and PC optimization in a randomly generated system topology. It is found that the mean delay in the whole network is significantly reduced. Besides, the standard deviation of user delay is much smaller. This means that the system has offered a much higher service fairness to all users. Table I shows the numerical comparison of transmission delay in the reference scenario and in the scenario where we performed our optimization. The results are based on an averaging over 200 random topologies. It is observed that both the mean delay and its standard deviation (s.d.) are significantly reduced (by more than 70%), in both systems (i)

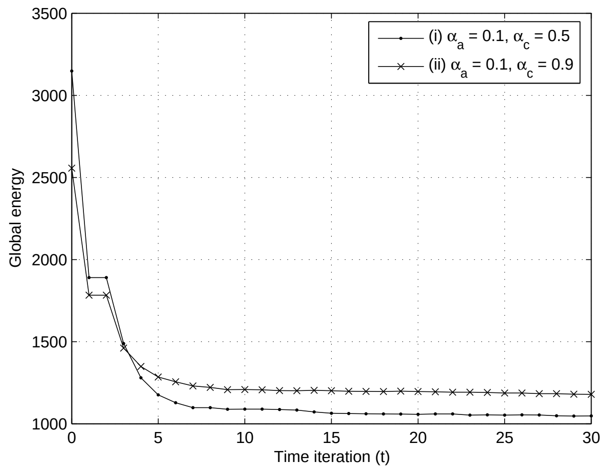

Fig. 3. The global energy $\mathcal{E}$ converges to the minimum quickly.

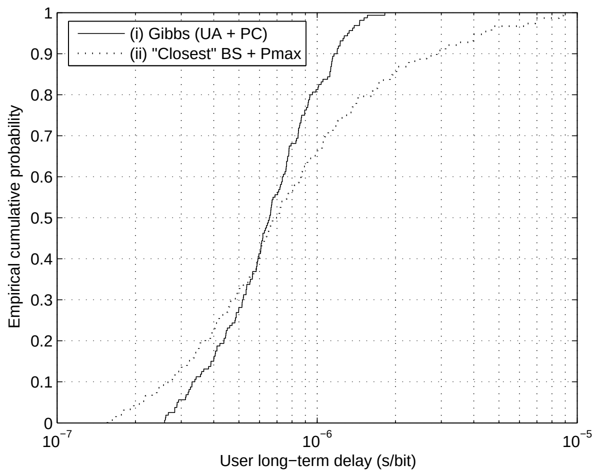

Fig. 4. Distribution of user long-term transmission delay in the system: (i) UA & PC by the proposed algorithm, and (ii) closest BS with constant transmission power $P_{\max}$.

and (ii). Besides, we investigate the system's power utilization efficiency in terms of system throughput normalized by total transmission power, in bits/s/W. The UA and PC optimization achieves a power utilization efficiency of more than 300% under both (i) and (ii).

VI. Conclusions

In this paper, we developed distributed algorithms for the self-optimization of cellular networks using Gibbs sampler. These algorithms are based on local measurements and on limited information exchange between BSs and users. The design does not require heavy coordination among the wireless devices and can adaptively drive the system to a state of minimal global potential delay. We discuss the scheme for power control and user association. A generalized framework with joint optimization is also provided. Numerical studies

TABLE I
User transmission delay before/after UA & PC optimization.

α_a, α_c	"Closest"+$P_{\max}$: mean, s.d.	Gibbs: mean, s.d.
i) 0.1, 0.5	2.8284, 1.5372 μs/bit	0.7145, 0.2932 μs/bit
ii) 0.1, 0.9	3.3087, 1.8959 μs/bit	0.8121, 0.2951 μs/bit

show that not only the mean delay but also its variance can be significantly reduced. Consequently, a higher level of service fairness among the users is offered. The performance is favorable to system-wide QoS enhancement and important to 3G/4G networks. An investigation of the proposed scheme in dynamic settings is in a future work.

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