Opportunistic Power Scheduling for Dynamic Multi-server Wireless Systems

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Abstract

In this paper, we present an *opportunistic power scheduling* scheme, i.e., a joint time-slot and power allocation scheme for downlink communication in wireless systems. Unlike past works, we allow multiple transmissions in a time-slot that could potentially interfere with each other. These multiple transmissions are allowed to achieve high system efficiency. Hence, it is important to not only select the mobiles to be scheduled in a time-slot, but also to allocate an appropriate transmission power level to these scheduled mobiles. We model the time-varying wireless channel as a stochastic process and formulate a stochastic optimization problem that attempts to maximize the expected total system utility with general constraints on performance or fairness. The power scheduling algorithm is obtained by using stochastic duality and implemented via stochastic subgradient techniques.

I. Introduction

The continued increase in demand for wireless services as well as the scarcity of radio resources makes it imperative to efficiently utilize network resources. A unique characteristic of wireless systems is that, due to fading and mobility, the wireless channel is time-varying and location-dependent.

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Although at first this appears to be a drawback, the variations in the channel condition can be exploited to improve network performance [1], [2], [3]. It is well known that the system throughput can be increased by giving a higher transmission priority to a mobile that is experiencing a better channel condition (e.g., a mobile that is closer to a base-station). However, as pointed out in [1], [2], [3], this naive strategy could result in a highly unfair resource allocation, thus potentially violating the performance or Quality of Service (QoS) requirements of some mobiles. Hence, one has to carefully consider the trade-off between system efficiency and fairness among mobiles when scheduling mobiles in wireless networks.

Recently, various “opportunistic” scheduling schemes have been developed for wireless networks (see [1], [2], [3], [4], [5], [6], [7], [8] and references therein). These schemes exploit the characteristics of the changing wireless channel and at the same time provide certain fairness or performance guarantees. We can classify these scheduling schemes as being either “single-server” scheduling or “multi-server” scheduling based on the underlying multiple access scheme used. In “single-server” scheduling, only one mobile is served at a time (e.g., a Time Division Multiple Access (TDMA) type of the multiple access scheme is used). For this class of scheduling schemes, a fixed power level is allocated to the scheduled mobile in the current time-slot. Hence, one only has to consider time-slot allocation without taking into account power allocation among mobiles. In contrast to “single-server” scheduling, in “multi-server” scheduling, multiple mobiles can be served simultaneously (e.g., a Code Division Multiple Access (CDMA) type of the multiple access scheme is used to allow simultaneous user transmissions). For this class of scheduling schemes, the transmission power of simultaneously scheduled mobiles could, in general, interfere with each other. Hence, one must also consider the problem of allocating power as well as choosing appropriate mobiles for transmission in the time-slot. Since the procedure to choose the candidate mobiles for transmission in a time-slot is equivalent to allocating zero power to unscheduled mobiles and positive power to the scheduled mobiles in the corresponding time-slot, we simply call this joint time-slot and power allocation *power scheduling*.

“Multi-server” transmission (e.g., CDMA) is adopted as a multiple-access scheme in third generation systems [9] and continues to be a strong candidate for future generation systems. Further, as shown in [10] and [11], except when all mobiles require very high data rates or experience poor channel conditions, we can improve system efficiency by simultaneously transmitting to multiple mobiles. The optimal number of these mobiles depends on the dynamic system environment. This implies that single-server scheduling can be inefficient because its selection is static in the sense of choosing only *one* mobile to be scheduled in a given time-slot. In contrast, in this paper, we will study the opportunistic scheduling problem for “dynamic multi-server” systems, where the number of mobiles selected for transmission can vary depending on the dynamic system characteristics.

Our work has similarity to works in [1], [2], [3], [4], [5], [6] in the sense that they model the channel condition as a stochastic process and develop appropriate scheduling strategies. However, in [1], [2], [3], [4], “single-server” scheduling problems are studied. Hence, only *mobile selection* problems are considered (i.e., which mobiles should be scheduled to transmit in a given time-slot) without considering what power should be allocated to each mobile while in our problem, we must decide which and how many mobiles should be scheduled and what power level should be allocated to each of the scheduled mobiles in a given tim-slot. In [5], static “multi-server” scheduling, in which the number of scheduled mobiles is fixed in each time-slot is studied. Moreover, since mobiles that are selected for transmission are assumed to communicate using independent interfaces with each other, only a *mobile selection* problem is considered. In [6], a scheduling problem that attempts to maximize the total expected throughput with constraints on fairness and maximum total transmission power is studied. Since multiple mobiles can be scheduled in a time-slot and the total transmission power is limited, both mobile selection and power allocation are considered. However, in [6], each link is assumed to be orthogonal and not to interfere with each other. Further, it is assumed that there is a linear relationship between the scheduled rate and the power consumed. These assumptions are not required in our work. Moreover, in [6], only utility based fairness is considered for scheduling, while, in our work, more general types of constraints (e.g., minimum performance, utility based fairness, and resource based fairness) can be easily accommodated.

The paper is organized as follows. In Section II, we introduce the system model. In Section III, we present our scheduling algorithm with general fairness or performance constraints and in Section IV, we provide some examples for the constraints. In Section V, we discuss non-convexity issues. We provide numerical results in Section VI and conclude in Section VII.

II. System Model

We focus on the downlink of a cell that consists of a single base-station and M mobiles. We assume that the wireless system is time-slotted. A time-slot in our system is an arbitrary interval of time and could consist of one packet or several packets. In each time-slot, mobiles are selected for transmission and the transmission power for each selected mobile is determined. The base-station has a maximum transmission power limit, P_T.

In wireless systems, the channel condition of each mobile (i.e., interference, background noise, and path gain) is time-varying and can be modeled as a stochastic process. We allow the channel condition to vary across time-slots and model it as a stationary stochastic process. In a time-slot, the system is assumed to be in one of several possible states, in which each state represents one of several possible levels of channel conditions for all mobiles. Each state takes a value from a finite set $\{1, 2, \cdots, S\}$[1]. We denote the probability that the system is in state s as π_s. We first define the "generic" signal quality for mobile i when the system is in state s as

$$\gamma_{s,i}(\bar{P}_s) = \frac{N_i G_{s,i} P_{s,i}}{\theta G_{s,i}(\sum_{j=1}^{M} P_{s,j} - P_{s,i}) + I_{s,i}}, \tag{1}$$

where

- $\bar{P}_s$: power allocation vector for all mobiles when the system is in state s.
- $P_{s,i}$: power allocation for mobile i when the system is in state s.
- N_i: a constant for mobile i.
- $G_{s,i}$: path gain from the base-station to mobile i when the system is in state s.
- $I_{s,i}$: background noise and intercell interference at mobile i when the system is in state s.
- θ: orthogonality factor.
- M: number of mobiles in the cell.

[1] Note that this assumption is not restrictive, since in a real system, the channel condition of a mobile is mapped into a level set with a finite number of levels by using quantization.

In this equation, if $N_i = 1$, then the signal quality metric $\gamma_{s,i}$ represents the signal to interference and noise ratio (SINR) for mobile i. If N_i is the processing gain for mobile i, which is defined by W/R_i, where W is the chip rate and R_i is the data rate, then $\gamma_{s,i}$ represents the bit energy to interference density ratio of mobile i, $(E_b/I_0)_{s,i}$ in the CDMA system, and if $N_i = W$, then $\gamma_{s,i} = (E_b/I_0)_{s,i}R_i$ of mobile i in the CDMA system.

The utility function U_i represents the degree of mobile i's satisfaction to the received signal quality. It could, for example, represent the throughput, a function of throughput, and the cost of power, etc. We assume that the utility function, U_i, is an increasing and continuous function of $\gamma_{s,i}$, bounded above, and $U_i(0) = 0$.

Remark 1: In some cases, the utility function could be a discrete function due to the discrete nature of the rate adaptation. However, in this case, the optimization problem is formulated as an integer optimization problem, which in general requires a much more complex algorithm than its continuous counterpart. Hence, it would be a more appropriate approach to solve the problem approximating the discrete function with the continuous function rather than to directly solve the integer optimization problem. Hence, in this paper, we assume that the utility function is continuous.

Remark 2: In this paper, we assume that the base-station always has packets to transmit to all users, as in the most of the previous works [1], [2], [3], [4], [5], [6]. In general, the base-station is connected with the high speed Internet and the wireless link is could be a bottleneck link in the downlink communication. Hence, in most of the time, the base-station has packets to transmit to the users and our assumption could be a good approximation to it.

III. Opportunistic Power Scheduling

The goal of this paper is to obtain the power scheduling solution for each mobile such that the expected total system utility (i.e., the sum of the expected utilities of all mobiles) under appropriate performance or fairness constraints is maximized. In this section, we first study the problem with general constraints and, in the next section, we will further investigate some relevant special cases.

The opportunistic power scheduling problem is formulated as

$$\text{(P)} \qquad \max \sum_{s=1}^{S} \pi_s \sum_{i=1}^{M} U_{s,i}(P_{s,i})$$
$$\text{s. t.} \quad \sum_{s=1}^{S} \pi_s g_{s,i}(\bar{P}_s) \geq K_i, \quad i = 1, 2, \cdots, M,$$
$$\bar{P}_s \in X_s, \qquad s = 1, 2, \cdots, S,$$

where $\bar{P}_s = (P_{s,1}, P_{s,2}, \cdots, P_{s,M}),\ X_s = \{(x_{s,1}, x_{s,2}, \cdots, x_{s,M}) \mid \sum_{i=1}^{M} x_{s,i} \leq P_T,\ 0 \leq x_{s,i} \leq P_T,\ i = 1, 2, \cdots, M\}$, $U_{s,i}(P_{s,i}) \stackrel{\triangle}{=} U_i(\gamma_{s,i}(P_{s,i}))$, and π_s is the probability that the system is in state s. It is clear that to maximize the total system utility, the base-station always has to transmit at its maximum transmission power limit, i.e., $\sum_{i=1}^{M} P_{s,i} = P_T$ [12], [13]. Hence, we can redefine $\gamma_{s,i}(\bar{P}_s)$ in (1) as

$$\gamma_{s,i}(P_{s,i}) \stackrel{\triangle}{=} \frac{N_i G_{s,i} P_{s,i}}{\theta G_{s,i}(P_T - P_{s,i}) + I_{s,i}}.$$

In this problem, $\sum_{s=1}^{S} \pi_s g_{s,i}(\bar{P}_s) \geq K_i$ could either be a performance or fairness constraint for mobile i. We assume that $g_{s,i}$ is bounded. Even though the utility of a mobile depends only on its own power scheduling (i.e., its own SINR), we allow the constraint on each mobile to depend not only on its own power scheduling but also on the power scheduling of the other mobiles.

Remark 3: For simplicity, in this section, we assume that $U_{s,i}(P_{s,i})$ is a strictly concave function and $g_{s,i}(\bar{P}_s)$ is a concave and continuous function. We will study the more general case in Section V.

The power scheduling problem (P) is formulated as a stochastic optimization problem [14], [15]. We assume that there exists at least a feasible solution (i.e., the solution that satisfies the constraints) to the above problem. Note that if the problem has a relative performance or fairness constraint (such as the utility based fairness constraint or the resource based fairness constraint discussed in the next section), feasibility is always guaranteed. However, if the problem has an absolute constraint, such as the minimum performance constraint studied in the next section, in general, we cannot guarantee feasibility. In this case, feasibility can be achieved by adopting an appropriate admission control strategy. The development of such a strategy is outside the scope of this paper. Instead, in this paper, we assume that the system has an admission control policy in place that ensures feasibility and focus on the scheduling problem.

In problem (P), if we knew the underlying probability distribution for the state of the system (i.e., π_s, $\forall s$), the problem could be equivalent to a deterministic convex optimization problem that can easily be solved. However, in practice, we do not have such a priori knowledge. Thus, we need to develop an algorithm that will work even without such a priori knowledge of the underlying probability distribution for the state of the system. To this end, we consider the dual of problem (P) and implement the power scheduling algorithm by using a stochastic subgradient algorithm. We define a Lagrangian function associated with problem (P) as

$$L(\bar{\mu}, \bar{P}) = \sum_{s=1}^{S} \pi_s \sum_{i=1}^{M} U_{s,i}(P_{s,i}) + \sum_{i=1}^{M} \mu_i (\sum_{s=1}^{S} \pi_s g_{s,i}(\bar{P}_s) - K_i),$$

where $\bar{P} = (\bar{P}_1, \bar{P}_2, \cdots, \bar{P}_S)$ and $\bar{\mu} = (\mu_1, \mu_2, \cdots, \mu_M)$. Then, the dual of problem (P) is defined as:

$$\text{(D)} \qquad \min_{\bar{\mu} \geq \bar{0}} F(\bar{\mu})$$

where

$$F(\bar{\mu}) = \max_{\bar{P} \in X} L(\bar{\mu}, \bar{P}) \tag{2}$$

and $X = \{(\bar{x}_1, \bar{x}_2, \cdots \bar{x}_S) \mid \bar{x}_s \in X_s,\ s = 1, 2, \cdots, S\}$. To solve problem (D), we first consider the problem in (2). For a given $\bar{\mu}$, the problem is separable in s and, thus, $\bar{P}(\bar{\mu})$ maximizes $L(\bar{\mu}, \bar{P})$ if and only if $\bar{P}(\bar{\mu}) = (\bar{P}_1(\bar{\mu}), \bar{P}_2(\bar{\mu}), \cdots, \bar{P}_S(\bar{\mu}))$, where

$$\bar{P}_s(\bar{\mu}) = \arg \max_{\bar{P}_s \in X_s} \{\sum_{i=1}^{M} U_{s,i}(P_{s,i}) + \mu_i g_{s,i}(\bar{P}_s)\},\ s = 1, 2, \cdots, S. \tag{3}$$

For a given $\bar{\mu}$ and system state s, the problem in (3) is a deterministic convex optimization problem. Hence, we can easily solve it without knowledge of the underlying probability distribution.

We now solve the dual problem (D). Note that $F(\bar{\mu})$ is a convex function of $\bar{\mu}$ and, thus, problem (D) is a stochastic convex optimization problem. Hence, we use a stochastic subgradient method [15], [16], which is defined by the following iterative process:

$$\mu_i^{(n+1)} = [\mu_i^{(n)} - \alpha^{(n)} v_i^{(n)}]^+,\ i = 1, 2, \cdots, M, \tag{4}$$

where $[a]^+ = \max\{0, a\}$ and $v_i^{(n)}$ is a random variable. Let the sequence of solutions, $\bar{\mu}^{(0)}, \bar{\mu}^{(1)}, \cdots, \bar{\mu}^{(n)}$, be generated by (4) and $\bar{v}^{(n)} = (v_1^{(n)}, v_2^{(n)}, \cdots, v_M^{(n)})$ be chosen such that

$$E\{\bar{v}^{(n)} \mid \bar{\mu}^{(0)}, \mu^{(1)}, \cdots, \mu^{(n)}\} = \partial_{\bar{\mu}} F(\bar{\mu}^{(n)}),$$

where $\partial_{\bar{\mu}} F(\bar{\mu}^{(n)})$ is a subgradient of $F(\bar{\mu})$ with respect to $\bar{\mu}$ at $\bar{\mu} = \bar{\mu}^{(n)}$. Then, the vector $\bar{v}^{(n)}$ is called a stochastic subgradient of $F(\bar{\mu})$ with respect to $\bar{\mu}$ at $\bar{\mu} = \bar{\mu}^{(n)}$. In this case, by solving (4), $\bar{\mu}^{(n)}$ converges to $\bar{\mu}^o$, the optimal solution of problem (D), with probability 1, if the following conditions are satisfied:

$$E\{||\bar{v}^{(n)}||^2 \mid \bar{\mu}^{(0)}, \mu^{(1)}, \cdots, \mu^{(n)}\} \leq c \tag{5}$$

for a constant c and

$$\alpha^{(n)} \geq 0, \ \sum_{n=0}^{\infty} \alpha^{(n)} = \infty, \text{ and } \sum_{n=0}^{\infty} (\alpha^{(n)})^2 < \infty. \tag{6}$$

To apply the stochastic subgradient method to solve problem (D), we need to know a stochastic subgradient of $F(\bar{\mu})$, $\partial_{\bar{\mu}} F(\bar{\mu})$. By Danskin's Theorem [17], $\partial_{\bar{\mu}} F(\bar{\mu})$ is obtained by

$$\partial_{\bar{\mu}} F(\bar{\mu}) = (d_1, d_2, \cdots, d_M), \tag{7}$$

where

$$d_i = \sum_{s=1}^{S} \pi_s g_{s,i}(\bar{P}_s(\bar{\mu})) - K_i, \ i = 1, 2, \cdots, M,$$

and $\bar{P}_s(\bar{\mu}) = (P_{s,1}(\bar{\mu}), P_{s,2}(\bar{\mu}), \cdots, P_{s,M}(\bar{\mu}))$ is a solution of the problem in (3). Hence, we can take

$$v_i^{(n)} = g_{s^{(n)},i}(\bar{P}_{s^{(n)}}(\bar{\mu}^{(n)})) - K_i, \ i = 1, 2, \cdots, M, \tag{8}$$

where $s^{(n)}$ is an index of the system state at iteration n. Then, since we assume that $g_{s^{(n)},i}$ is bounded, the condition in (5) is satisfied and, thus, the algorithm in (4) converges to the optimal solution that solves problem (D) with a sequence of step-sizes that satisfies the conditions given in (6) such as $\alpha^{(n)} = 1/n$. Since the primal problem (problem (P)) is a convex optimization problem, there is no duality gap between it and its dual (problem (D)). Hence, the algorithm also converges to the optimal power scheduling. Note that our subgradient method does not require knowledge of the underlying probability distribution π_s.

A. Problem with Separable Constraints

In many cases (see examples in the next section), the performance or fairness constraint $g_{s,i}(\bar{P}_s)$ for each user i can be separable, i.e., the constraint can be represented as

$$g_{s,i}(\bar{P}_s) = \sum_{j=1}^{M} a_{i,j} g_{s,i}^{j}(P_{s,j}),\ \forall i. \tag{9}$$

In this case, the problem in (3) can be rewritten by

$$\bar{P}_s(\bar{\mu}) = \arg\max_{\bar{P}_s \in X_s} \{\sum_{i=1}^{M} U_{s,i}^{ad}(\bar{\mu}, P_{s,i})\}, \tag{10}$$

where

$$U_{s,i}^{ad}(\bar{\mu}, P_{s,i}) = U_{s,i}(P_{s,i}) + \sum_{j=1}^{M} \mu_j a_{j,i} g_{s,j}^{i}(P_{s,i}). \tag{11}$$

For a given $\bar{\mu}$ and system state s, $U_{s,i}^{ad}(\bar{\mu}, P_{s,i})$ for user i can be represented as a function of its own power allocation, as in the original utility function. We call $U_{s,i}^{ad}(\bar{\mu}, P_{s,i})$ the adjusted utility function of mobile i. Hence, in this case, by solving (10), we obtain a power allocation that maximizes the sum of the adjusted utilities, $U_{s,i}^{ad}(\bar{\mu}, P_{s,i})$'s, of all mobiles with a constraint only on the total transmission power limit of the base-station.

B. Implementation

To implement the opportunistic power scheduling scheme, each mobile needs to inform the base-station of its utility function when a call is initiated. In each time-slot, the base-station selects mobiles to be currently scheduled and determines the transmission power level for these mobiles in the following way. In time-slot n, each mobile measures its path gain and interference, and sends this information to the base-station. By using the measured data, the base-station can know the system state in the time-slot and calculate the power allocation vector in the time-slot $\bar{P}^{*}_{s^{(n)}}$ by solving the problem in (3) with $\bar{\mu} = \bar{\mu}^{(n)}$ and $s = s^{(n)}$, where $\bar{\mu}^{(n)}$ is obtained by (4) and $s^{(n)}$ is the system state in the time-slot. Since for a given $\bar{\mu}^{(n)}$ and system state $s^{(n)}$, the problem in (3) is a deterministic convex optimization problem, it can be easily solved by using standard convex optimization techniques such as Karush-Kuhn-Tucker (KKT) conditions and the duality theorem. Further, based on the power allocation in the current time-slot, the value of $\bar{\mu}^{(n+1)}$ for the next time-slot is updated by using a stochastic subgradient method in (4).

If the constraint for each mobile is separable, as in the previous subsection, we can interpret the power scheduling procedure as follows. As shown in the previous subsection, by solving (10) in each time-slot, power is allocated to mobiles such that the sum of the adjusted utilities of the mobiles is maximized without considering the performance or fairness constraint of each mobile. In this case, the constraint on each mobile can be achieved by the appropriate adjusted utility function (i.e., by the appropriate μ_i) for each mobile.

IV. EXAMPLES

In this section, we consider the following typical constraints that are important in providing adequate quality transmission to the mobiles. These are: the minimum performance constraint, the utility based fairness constraint, and the resource based fairness constraint.

A. Minimum performance constraint

In this power scheduling problem, each mobile i has a constraint on its minimum expected utility, C_i, which is formulated as

$$\sum_{s=1}^{S} \pi_s U_{s,i}(P_{s,i}) \geq C_i,\ i = 1, 2, \cdots, M.$$

Hence, $K_i = C_i$ and $g_{s,i}(\bar{P}_s)$ is separable and represented by (9) with

$$a_{i,j} = \begin{cases} 1, & \text{if } i = j \\ 0, & \text{otherwise} \end{cases} \quad \text{and } g^j_{s,i}(P_{s,j}) = \begin{cases} U_{s,i}(P_{s,i}), & \text{if } i = j \\ 0, & \text{otherwise} \end{cases}.$$

Therefore, from (11), the adjusted utility function for mobile i is obtained by multiplying a weight factor $1 + \mu_i$ to the original utility function as

$$U^{ad}_{s,i}(\bar{\mu}, P_{s,i}) = (1 + \mu_i) U_{s,i}(P_{s,i}).$$

Further, from (8), the stochastic subgradient is obtained by the difference between the achieved utility of the user in the current time-slot and its constraint as

$$v^{(n)}_i = U_{s^{(n)},i}(P_{s^{(n)},i}(\bar{\mu}^{(n)})) - C_i.$$

B. Utility Based Fairness Constraint

In this subsection, we consider an opportunistic power scheduling problem in which each mobile i is guaranteed to achieve at least a fraction w_i of the expected total system utility. This constraint is formulated as

$$\sum_{s=1}^{S} \pi_s U_{s,i}(P_{s,i}) - w_i \sum_{s=1}^{S} \pi_s \sum_{j=1}^{M} U_{s,j}(P_{s,i}) \geq 0,$$

where $w_i \geq 0$, and $\sum_{i=1}^{M} w_i \leq 1$. Hence, $K_i = 0$ and $g_{s,i}(\bar{P}_s)$ is separable and represented by (9) with

$$a_{i,j} = \begin{cases} 1 - w_i, & \text{if } i = j \\ -w_i, & \text{otherwise} \end{cases} \quad \text{and } g_{s,i}^{j}(P_{s,j}) = U_{s,j}(P_{s,j}).$$

Again, from (11), we obtain the adjusted utility function

$$U_{s,i}^{ad}(\bar{\mu}, P_{s,i}) = (1 + \mu_i - \sum_{j=1}^{M} \mu_j w_j) U_{s,i}(P_{s,i}),$$

which is obtained by multiplying a weight factor $1 + \mu_i - \sum_{j=1}^{M} \mu_j w_j$ to the original utility function. Further, from (8) the stochastic subgradient is obtained as

$$v_i^{(n)} = U_{s^{(n)},i}(P_{s^{(n)},i}(\bar{\mu}^{(n)})) - w_i \sum_{j=1}^{M} U_{s^{(n)},j}(P_{s^{(n)},i}(\bar{\mu}^{(n)})),$$

which is the difference between the achieved utility of the user and its constraint based on power allocation in the current time-slot.

C. Resource Based Fairness Constraint

Here, each mobile i is guaranteed to consume resource (power) by an amount that is at least h_i fraction of the total amount of resource (i.e., h_i fraction of the total transmission power), which is formulated by

$$\sum_{s=1}^{S} \pi_s P_{s,i} - h_i \sum_{s=1}^{S} \pi_s \sum_{j=1}^{M} P_{s,j} = \sum_{s=1}^{S} \pi_s P_{s,i} - h_i P_T \geq 0, \ i = 1, 2, \cdots, M,$$

where $h_i \geq 0$ and $\sum_{i=1}^{M} h_i \leq 1$. Hence, $K_i = 0$ and $g_{s,i}(\bar{P}_s)$ is separable and represented by (9) with

$$a_{i,j} = \begin{cases} 1 - h_i, & \text{if } i = j \\ -h_i, & \text{otherwise} \end{cases} \quad \text{and } g_{s,i}^{j}(P_{s,j}) = P_{s,j}.$$

From (8) and (11), the adjusted utility function for mobile is obtained as

$$U_{s,i}^{ad}(\bar{\mu}, P_{s,i}) = U_{s,i}(P_{s,i}) + \mu_i P_{s,i},$$

which is achieved by adding an offset value $\mu_i P_{s,i}$ to the original utility function and the stochastic subgradient is obtained as

$$v_i^{(n)} = P_{s^{(n)},i}(\bar{\mu}^{(n)}) - h_i P_T,$$

which is the difference between the amount of power that is allocated to the user in the current time-slot and its constraint.

V. Non-convexity and Complexity Issues

Thus far, we have developed an opportunistic power scheduling algorithm under a convex optimization framework, i.e., we have assumed that $U_{s,i}$ is a strictly concave function and $g_{s,i}(\bar{P}_s)$ is a concave function. This allows us to use a dual approach to obtain the optimal power scheduling solution, since there is no duality gap between the primal and its dual. In this section, we will weaken this assumption to reflect the fact that utility functions of interest may not be concave, but in fact sigmoidal [12], [13]. In this case, the problem could be a non-convex optimization and there might be a duality gap between the primal problem and its dual. Hence, the dual approach may not result in an optimal solution to the primal problem. However, as we show in the next proposition, as the randomness in the system increases, the duality gap decreases. Hence, as the randomness of the system increases (i.e., as we have a finer granularity of the quantization for the channel condition of each mobile), we can achieve a better approximation of the optimal power scheduling by solving the dual problem.

Proposition 1: Let $\sup(P)$ *be the optimal value of problem (P) and* $\inf(D)$ *be the optimal value of the corresponding dual problem. If* $\sup_s \pi_s \sum_{i=1}^{M} U_{s,i}(P_{s,i}) \to 0$ *and* $\sup_s \pi_s g_{s,i}(\bar{P}_s) \to 0$ *as* $S \to \infty$*, then* $\sup(P) - \inf(D) \to 0$ *as* $S \to \infty$.

Proof: See Appendix. ■

From this result, we deduce that when the randomness of the system is large, the same power scheduling algorithm that has been developed in this paper can be used to obtain a good approximation to the optimal solution.

Note that the main complexity of our algorithm comes from that we must solve the optimization problem in (3), (or the problem in (10), if constraints are separable) in each time-slot. If the problem is convex, then it can be solved by using simple standard algorithms such as a gradient projection algorithm and a penalty approach. However, when we have non-concave utility functions, it is a non-convex optimization problem, which is in general difficult to solve. In our previous work [12], [13], we have developed a power allocation algorithm by considering a similar problem to the problem in (10) with three types of utility functions: concave, convex, and sigmoidal-like functions. This algorithm provides asymptotically (in the number of mobiles) optimal power allocation that is shown to be a good approximation of the optimal power allocation even with the moderate number of mobiles. Hence, if the constraint for each user is separable and the adjusted utility function of each user is represented by one of those three types of functions (this condition is satisfied for each power scheduling in the previous section if the utility function of each user is represented by one of those three types of functions), we can obtain a good approximation of the optimal solution of the problem in (10) by using the algorithm that we previously developed in [12], [13]. The algorithm consists of two stages: the mobile selection stage where the base-station selects mobiles and the power allocation stage where the base-station allocates power to the selected mobiles. The complexity of the mobile selection stage is $O(M)$ and at the power allocation stage, the problem is reduced to a simple convex optimization problem. Hence, our algorithm can be easily implemented.

VI. Numerical Results

In this section, we provide numerical results to illustrate various features of our power scheduling scheme. We consider a CDMA system that consists of nine square cells, as in Fig. 1. We assume that the base-station is located at the center of the cell and each base-station always transmits at its maximum transmission power limit, P_T. We focus on the center cell of the system. We model the path gain from the base-station to mobile i, $G_{s,i}$, as

$$G_{s,i} = \frac{D_{s,i}}{t_i^{\alpha}}, \tag{12}$$

where t_i is the distance from the base-station to mobile i, α is a distance loss exponent, and $D_{s,i}$ is a log-normally distributed random variable with mean 0 and variance σ^2 (dB), which represents shadowing [18]. We let $P_T = 10$, $\alpha = 4$, $\theta = 1$, and the length of the side of the cell be 1000. We assume that mobile i has a sigmoidal utility function that is non-concave and is expressed by

$$U_i(\gamma_i) \quad = \quad c_i\{\frac{1}{1+e^{a_i(\gamma_i - b_i)}} - d_i\},$$

where we set $c_i = \frac{1+e^{a_i b_i}}{e^{a_i b_i}}$ and $d_i = \frac{1}{1+e^{a_i b_i}}$ for normalization (i.e., $U(0) = 0$ and $U(\infty) = 1$). For each experiment, we run the simulation program for 10^4 time-slots and provide $\bar{\mu}^{(n)}$ in the last time-slot, i.e., $\bar{\mu}^{(10^4)}$ and the (time) average value of the utility for each mobile i, U_i^a and the average value of the total system utility, U_T^a, which are defined as

$$U_i^a = \frac{1}{10^4}\sum_{n=1}^{10^4} U_i^{(n)},$$

where $U_i^{(n)}$ is the achieved utility of mobile i in time-slot n, and

$$U_T^a = \frac{1}{10^4}\sum_{i=1}^{M}\sum_{n=1}^{10^4} U_i^{(n)},$$

where M is the number of mobiles.

In the first experiment, we simulate our opportunistic power scheduling scheme with minimum performance constraints. We assume that there are five mobiles with the same utility function. We set $a_i = 1$, $b_i = 7$, $N_i = 32$, and $C_i = 0.503$ for all mobiles, and $\sigma = 4$ dB. We assume that mobile i has a fixed distance $t_i = 100 \times i$ from the base-station. Hence, mobile 1 is closest and mobile 5 is farthest from the base-station. This implies that, in general, mobile i has a better channel condition than mobile j, if $i < j$. We also compare the performance of our opportunistic power scheduling scheme with those of two other schemes. In the non-opportunistic power scheduling scheme, in each time-slot, power is allocated to each mobile so that they achieve the same utility (however, the power allocation is done such that this is the maximum possible utility value). Hence, in this scheme, the time-varying channel condition of each mobile is not exploited. In the greedy power scheduling scheme, in each time-slot, power is allocated to each mobile so that the system utility of the time-slot can be maximized. This can be achieved by solving the problem in (10) with the original utility function for each mobile (i.e., $\mu_i = 0$, $\forall i$) in each time-slot. Hence, in this scheme, the minimum performance constraint of each mobile is not considered.

We provide the average utility of each mobile and the average total system utility for each power scheduling scheme in Table I. As this table shows, in the non-opportunistic scheduling scheme, each mobile achieves the same average utility. However, since it does not exploit the time-varying channel condition of each user, it results in the lowest average total system utility. The greedy scheduling scheme provides the highest average total system utility, but it does not satisfy the minimum performance constraint for some mobiles (e.g., it violates the minimum performance constraint for mobile 5). Compared with the other two schemes, our opportunistic power scheduling scheme satisfies the minimum performance constraint of each mobile without a significant loss of efficiency.

In Table II, we also provide the value of μ_i for each mobile i in time-slot 10^4. The table shows that μ_1, μ_2, and μ_3 converge to zero, as these correspond to the μ_i values of mobiles 1, 2, and 3, all of which more than satisfy their minimum performance constraints. However, μ_4 and μ_5 are strictly positive as their corresponding mobiles just barely satisfy their minimum performance constraints. The reason for this result can be explained as follows. As shown in the previous section, our algorithm is equivalent to solving the problem in (10) in each time-slot that attempts to maximize the weighted sum of all mobiles' utilities without minimum performance constraints. The constraints are satisfied with an appropriate weight factor for each mobile. In this experiment, if each mobile has a unit weight factor (i.e., $\mu_i = 0$, $\forall i$), the minimum performance constraint of mobile 5 cannot be satisfied (see greedy scheduling in Table I). Hence, to satisfy the minimum performance constraint of mobile 5, the weight factor of mobile 5 (i.e., μ_5) must be increased. By increasing the weight factor, more power can be scheduled to mobile 5, thus improving its performance. Further, since this violates the minimum performance constraint of mobile 4, the weight factor of mobile 4 (i.e., μ_4) is also increased. In this case, since mobile 5 experiences a worse channel condition than mobile 4, mobile 5 needs a larger weight factor (i.e., a larger value of μ_i) than that of mobile 4 to meet its performance constraint. However, for system efficiency, the weight factors of mobiles 4 and 5 must be increased up to the values with which their minimum performance constraints are barely satisfied. On the other hand, the weight factors for the other mobiles that satisfy their minimum performance constraints with strict inequality are not increased, since their minimum performance constraints can be satisfied even without increasing their weight factors.

In the second experiment, we simulate our opportunistic power scheduling scheme with utility based fairness constraints considering the same system, as in the previous experiment. We provide the results for $w_i = 0.2$ and $w_i = 0.1$ for each mobile, respectively. We also compare the performance of our opportunistic power scheduling scheme with those of greedy and non-opportunistic scheduling schemes. Note that when $w_i = 0.2$, each mobile must achieve the same average utility and, thus, both our opportunistic power scheduling scheme and the non-opportunistic power scheduling scheme have the same fairness constraint.

We provide the average utility of each mobile and the average total system utility for each scheme in Table III and μ_i of each mobile i in the last time-slot for our opportunistic power scheduling scheme in Table IV. As the results show, the greedy power scheduling scheme does not satisfy the constraint for some mobiles while it provides the highest average total system utility. When $w_i = 0.2$ for each mobile, both our opportunistic power scheduling and non-opportunistic power scheduling satisfy the constraint of each mobile. However, since our opportunistic power scheduling scheme exploits the variations of the channel condition, it provides a higher average utility to each individual mobile and, thus, a higher average total system utility than the non-opportunistic power scheduling scheme. In our opportunistic power scheduling, the system with $w_i = 0.1$ has a looser fairness constraint than the system with $w_i = 0.2$. Hence, the former has more freedom to use power to increase the efficiency of the system than the latter, which results in the increase in the average total system utility.

Table IV shows that, as in the previous experiment, only mobiles that barely satisfy their fairness constraints have a positive μ_i and to meet its constraint the mobile with a worse channel condition has a higher weight factor than the mobile with a better channel condition.

In the third experiment, we simulate our opportunistic scheduling scheme with resource based fairness constraints. In this simulation, we assume that each mobile has a different utility function but the same distance from the base-station. We set $N_i = 32$, $a_i = 1$, and $b_i = 5 + i$ for mobile i. In this case, in general, a mobile with a larger value of b_i requires more power to achieve the same utility than a mobile with a smaller value of b_i. Hence, we can infer that mobile i is more efficient than mobile j, if $i < j$. We provide the results for $h_i = 0.2$ and $h_i = 0.15$ for each mobile, respectively. Note that when $h_i = 0.2$, each mobile must be allocated the same amount of power on average. We also compare the performance of our opportunistic power scheduling scheme with those of greedy and non-opportunistic scheduling schemes. In the non-opportunistic scheduling scheme, each mobile is allocated a power of P_T/M in each time-slot. Hence, it has the same fairness constraint as our opportunistic power scheduling scheme with $h_i = 0.2$. We provide the average utility of each mobile and the average total system utility for each scheme in Table V and the average allocated power level, P_i^a, for each mobile i in Table VI, which is defined as

$$P_i^a = \frac{1}{10^4} \sum_{n=1}^{10^4} P_i^{(n)},$$

where $P_i^{(n)}$ is the allocated power to mobile i in time-slot n. We also provide $\bar{\mu}^{(10^4)}$ in Table VII. These tables show similar results to those of previous experiments.

In Fig. 2, we compare the performance of our opportunistic power scheduling and that of non-opportunistic power scheduling by varying the standard deviation σ of $D_{s,i}$ in (12) for each constraint. A larger value of σ implies a larger fluctuation of the path gain between the mobile and the base-station. For the simulation with minimum performance constraints, we first simulate the non-opportunistic power scheduling and use the achieved utility of each mobile in this scheduling as the minimum performance constraint. For utility and resource based fairness constraints, we set $b_i = 0.2$ and $h_i = 0.2$, respectively. Hence, for each setup, our opportunistic power scheduling and non-opportunistic power scheduling have the same constraint. The results show that as σ increases, the performance gain of our opportunistic power scheduling schemes over non-opportunistic schemes increases. This implies that a larger fluctuation in the path gain results in a larger advantage to our opportunistic power scheduling scheme, providing a greater freedom to exploit the time-varying channel condition associated with each mobile.

Note that in the above experiments, the utility function of each mobile is normalized such that its maximum value is set be one. Hence, in “single-server” scheduling schemes that have been developed in [1], [2], [3], [4], the average total system utility for each constraint can be at most one, which is much lower than that of our “multi-server” scheduling scheme. To further illustrate the advantage of our “multi-server” scheduling scheme over a “single-server” scheduling scheme, we compare their performance in Tables VIII and IX. Here, both system have the same system parameters such as the same bandwidth, the same cell size, and so on. In these tables, we simulate each opportunistic scheduling scheme with utility based fairness constraints by varying the distance of the mobiles from the base-station. We generate five mobiles and set $a_i = 0.5$, $b_i = 11$, $N_i = 32$, and $w_i = 0.2$ for all mobile i. Each mobile is located at the same distance t from the base-station. As the distance t gets larger, the channel condition of each mobile gets worse. We compare the average number of selected mobiles in a time-slot (S^a) of each scheme, which is defined as

$$S^a = \frac{1}{10^4} \sum_{n=1}^{10^4} S^{(n)},$$

where $S^{(n)}$ is the number of selected mobiles for transmission in time-slot n in Table VIII, and the average total system utility of each scheme in Table IX. The results indicate that our “multi-server” scheduling scheme can adapt to various system environment by controlling the number of selected mobiles for simultaneous transmission in a time-slot. As the channel condition of each mobile gets better, our scheme selects more mobiles for simultaneous transmission in a time-slot and, thus, provides higher system efficiency than the “single-server” scheduling scheme.

VII. Conclusion

In this paper, we have developed an opportunistic power scheduling scheme in “multi-server” systems with general constraints on fairness or performance. This scheme exploits the time-varying channel condition of each mobile and determines, in each time-slot, which and how many mobiles should be scheduled for transmission and at what power level. We have formulated the problem as a stochastic optimization problem. But the main difficulty in solving this problem is that, in practice, we do not have a priory knowledge of the time-varying channel conditions of mobiles. Hence, in this paper, we have solved the problem by using stochastic duality and a stochastic subgradient method, and implemented the power scheduling algorithm that does not require such a priori knowledge.

The results show that our opportunistic power scheduling scheme is more efficient than non-opportunistic power scheduling that does not exploit the time-varying channel condition of each mobile. Moreover, compared with a "single-server" scheduling scheme, our "multi-server" scheduling scheme provides higher system efficiency by controlling the number of simultaneously scheduled mobiles in a time-slot by adapting to the system environment. The results also show that as the variation of channel condition gets larger, the relative efficiency of our opportunistic power scheduling over non-opportunistic power scheduling increases. While our solution always achieves optimality for concave utility functions, we have shown that even for non-concave utility functions, as the variation of channel condition gets larger, our power scheduling can provide a better approximation to the optimal power scheduling. Therefore, the time-varying channel condition of the mobile could be beneficial to efficient and fair power scheduling, if it is appropriately exploited.

APPENDIX

PROOF OF PROPOSITION 1

Let $f_s(\bar{P}_s) = \pi_s \sum_{i=1}^{M} U_{s,i}(P_{s,i})$, $h_s(\bar{P}_s) = \pi_s(g_{s,1}(\bar{P}_s), g_{s,2}(\bar{P}_s), \cdots, g_{s,M}(\bar{P}_s))$, and $b = (K_1, K_2, \cdots, K_M)$. Then, we can rewrite problem (P) as:

$$\begin{aligned} &\max \sum_{s=1}^{S} f_s(\bar{P}_s) \\ &\text{subject to} \quad \bar{P}_s \in X_s, \qquad s = 1, 2, \cdots, S \\ &\qquad\qquad\quad \textstyle\sum_{s=1}^{S} h_s(\bar{P}_s) \geq b \end{aligned}$$

The above is the same primal problem in Proposition 5.26 in [19] and we will prove this proposition in a similar way to the proof of Proposition 5.26 in [19]. We can easily show that the assumptions (A1) and (A2) of Proposition 5.26 in [19] are satisfied, i.e., there exists at least one feasible solution, X_s is compact, and f_s and h_s are continuous on X_s. However, note that the assumption (A3) of Proposition 5.26 in [19] may not be satisfied. Hence, the proof of Proposition 5.26 in [19] is not directly applicable for the proof of this proposition.

Since the assumptions (A1) and (A2) of Proposition 5.26 in [19] are satisfied, from the proof of

Proposition 5.26 in [19], there exist vectors $\bar{P}_s^j \in X_s$, $\bar{P}_s^*$ and scalars $\alpha_s^1, \alpha_s^2, \cdots, \alpha_s^{M+2}$ such that

$$\sum_{j=1}^{M+2} \alpha_s^j = 1,\ \alpha_s^j \geq 0,\ j = 1, 2, \cdots, M+2,$$

$$\sum_{s \notin \bar{S}} h_s(\bar{P}_s^*) + \sum_{j=1}^{M+2} \alpha_s^j h_s(\bar{P}_s^j) \geq b,$$

and

$$\sum_{s \notin \bar{S}} f_s(\bar{P}_s^*) + \sum_{j=1}^{M+2} \alpha_s^j f_s(\bar{P}_s^j) = \inf(D),$$

where $\bar{S}$ is a subset of $\{1, 2, \cdots, S\}$ with at most $M+1$ indices. By the definitions of h_s and f_s, and the assumption that $\sup_s \pi_s \sum_{i=1}^M U_{s,i}(P_{s,i}) \to 0$ and $\sup_s \pi_s g_{s,i}(\bar{P}_s) \to 0$, as $S \to \infty$,

$$\sum_{s=1}^{S} h_s(\bar{P}_s^*) = \sum_{s \notin \bar{S}} h_s(\bar{P}_s^*) + \sum_{s \notin \bar{S}} h_s(\bar{P}_s^*) \to \sum_{s \notin \bar{S}} h_s(\bar{P}_s^*),$$

$$\sum_{s=1}^{S} f_s(\bar{P}_s^*) = \sum_{s \notin \bar{S}} f_s(\bar{P}_s^*) + \sum_{s \notin \bar{S}} f_s(\bar{P}_s^*) \to \sum_{s \notin \bar{S}} f_s(\bar{P}_s^*),$$

$$\sum_{j=1}^{M+2} \alpha_s^j h_s(\bar{P}_s^j) \to 0,\ \text{and}\ \sum_{j=1}^{M+2} \alpha_s^j f_s(\bar{P}_s^j) \to 0,$$

as $S \to \infty$. Hence,

$$\sum_{s=1}^{S} h_s(\bar{P}_s^*) \geq b - \epsilon,\ ||\epsilon|| \to 0 \text{ and } \sum_{s=1}^{S} f_s(\bar{P}_s^*) \to \inf(D),$$

as $S \to \infty$. Further, by the weak duality theorem,

$$\sup(P) \leq \inf(D).$$

Hence, $\sup(P) - \inf(D) \to 0,$ as $S \to \infty$.

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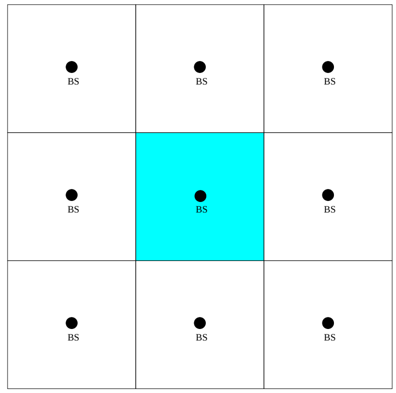

Fig. 1. Cellular network model.

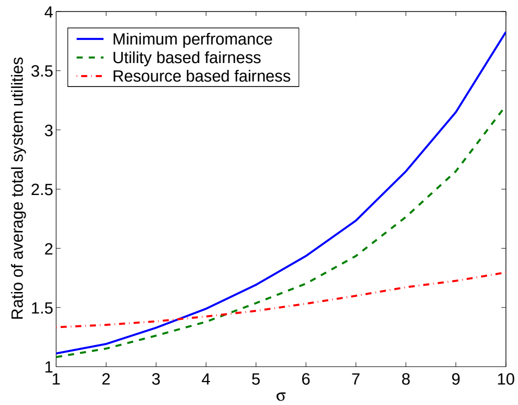

Fig. 2. The ratio of the total system utility of opportunistic power scheduling to that of non-opportunistic power scheduling.

TABLE I

COMPARISON OF AVERAGE UTILITIES (WITH MINIMUM PERFORMANCE CONSTRAINTS).

Mobile	1	2	3	4	5	Total
Non-opportunistic	0.503	0.503	0.503	0.503	0.503	2.515
Our opportunistic	0.975	0.963	0.805	0.502	0.505	3.750
Greedy	0.985	0.984	0.958	0.738	0.185	3.850

TABLE II

COMPARISON OF μ_i FOR EACH MOBILE (WITH MINIMUM PERFORMANCE CONSTRAINTS).

Mobile	1	2	3	4	5
μ_i	0	0	0	0.080	1.097

TABLE III

COMPARISON OF AVERAGE UTILITIES (WITH UTILITY BASED FAIRNESS CONSTRAINTS).

Mobile	1	2	3	4	5	Total
Non-opportunistic	0.503	0.503	0.503	0.503	0.503	2.515
Our opportunistic ($w_i = 0.2$)	0.694	0.694	0.692	0.694	0.695	3.469
Our opportunistic ($w_i = 0.1$)	0.982	0.979	0.913	0.564	0.384	3.822
Greedy	0.985	0.984	0.958	0.738	0.185	3.850

TABLE IV

COMPARISON OF μ_i FOR EACH MOBILE (WITH UTILITY BASED FAIRNESS CONSTRAINTS).

Mobile	1	2	3	4	5
μ_i ($w_i = 0.2$)	0.408	0.416	0.466	0.738	1.989
μ_i ($w_i = 0.1$)	0	0	0	0	0.471

TABLE V

COMPARISON OF AVERAGE UTILITIES (WITH RESOURCE BASED FAIRNESS CONSTRAINTS).

Mobile	1	2	3	4	5	Total
Non-opportunistic fair	0.847	0.716	0.515	0.305	0.146	2.529
Our opportunistic ($h_i = 0.2$)	0.854	0.787	0.719	0.647	0.596	3.603
Our opportunistic ($h_i = 0.15$)	0.903	0.868	0.794	0.602	0.467	3.634
Greedy	0.916	0.887	0.835	0.705	0.304	3.647

TABLE VI

COMPARISON OF AVERAGE POWER USAGES (WITH RESOURCE BASED FAIRNESS CONSTRAINTS).

Mobile	1	2	3	4	5	Total
Non-opportunistic	2	2	2	2	2	10
Our opportunistic ($h_i = 0.2$)	2.002	2.008	1.994	2.001	1.993	10
Our opportunistic ($h_i = 0.15$)	2.207	2.280	2.220	1.785	1.508	10
Greedy	2.264	2.353	2.355	2.082	0.946	10

TABLE VII

COMPARISON μ_i FOR EACH MOBILE (WITH RESOURCE BASED FAIRNESS CONSTRAINTS).

Mobile	1	2	3	4	5
μ_i ($h_i = 0.2$)	4.785	4.802	4.813	4.831	4.852
μ_i ($h_i = 0.15$)	0	0	0	0	0.019

TABLE VIII

COMPARISON OF AVERAGE NUMBERS OF SELECTED MOBILES AT A TIME-SLOT.

t	100	200	300	400	500
Multi-server	3	2.576	2	1.982	1.396
Single-server	1	1	1	1	1

TABLE IX

COMPARISON OF AVERAGE TOTAL SYSTEM UTILITIES.

t	100	200	300	400	500
Multi-server	2.769	2.435	2	1.974	1.375
Single-server	1	1	1	1	0.998