Joint Resource Allocation and Base-Station Assignment for the Downlink in CDMA Networks

Jang-Won Lee, *Member, IEEE*, Ravi R. Mazumdar, *Fellow, IEEE*, and Ness B. Shroff, *Senior Member, IEEE*

***Abstract*—In this paper, we jointly consider the resource allocation and base-station assignment problems for the downlink in CDMA networks that could carry heterogeneous data services. We first study a joint power and rate allocation problem that attempts to maximize the expected throughput of the system. This problem is inherently difficult because it is in fact a nonconvex optimization problem. To solve this problem, we develop a distributed algorithm based on dynamic pricing. This algorithm provides a power and rate allocation that is asymptotically optimal in the number of mobiles. We also study the effect of various factors on the development of efficient resource allocation strategies. Finally, using the outcome of the power and rate allocation algorithm, we develop a pricing-based base-station assignment algorithm that results in an overall joint resource allocation and base-station assignment. In this algorithm, a base-station is assigned to each mobile taking into account the congestion level of the base-station as well as the transmission environment of the mobile.**

***Index Terms*—Base-station assignment, CDMA networks, nonconvex optimization, power and rate allocation, pricing.**

I. Introduction

THE increasing demand for high data rate services in wireless networks and the scarcity of radio resources necessitate the efficient use of radio resources. The time-varying system environment, such as time and location dependent channel conditions, and the demand to accommodate mobiles with diverse service requirements are some of the main difficulties in efficiently using radio resources. Hence, it is necessary to develop a resource allocation scheme that takes into account the time-varying system environment and the service requirements of mobiles. Moreover, if joint allocation of resources is considered, the performance of the system could be significantly improved.

Recently, there have been a number of papers that have studied joint resource allocation problems [1]–[7]. Oh and Wasserman [1] consider a joint power and spreading gain allocation problem for the uplink of a single cell in code division multiple access (CDMA) networks. They formulate an optimization problem for a single class of mobiles with a constraint on the maximum transmission power of each mobile. In this work, they do not impose any constraint on the minimum spreading gain (i.e., the maximum data rate). They show that for the optimal solution, mobiles are selected for transmission according to the channel condition, and if a mobile is selected, it transmits at its maximum transmission power. They generalize their algorithm to multi-cellular networks in [2]. Their algorithm can be easily modified for the downlink problem. In this case, the optimal strategy is selecting only one mobile that is in the best transmission environment at a time and allocating the maximum transmission power to that mobile (i.e., the time division multiple access (TDMA) type of strategy). Bedekar *et al.* [3] and Berggren *et al.* [4] consider joint power and rate allocation for the downlink of the CDMA system with a constraint on the maximum transmission power for the base-station. However, their models do not consider that each mobile could have a maximum data rate constraint. Their results also show that, in this case, the TDMA type of strategy is an optimal multiple access strategy. This strategy is used in the IS-856 system [8], which is also known as high data rate (HDR) [9], [10].

Joint power allocation and base-station assignment problems for the uplink have been considered by Hanly [5] and Yates and Huang [6]. In these papers, the minimum transmission power satisfying the signal to interference and noise ratio (SINR) threshold of each mobile is obtained via a strategy employing both power allocation and base-station assignment. Saraydar *et al.* [7] also consider a joint power allocation and base-station assignment problem for the uplink. They model the problem as an N-person noncooperative power allocation game. Each mobile selects the optimal power level and the base-station that maximize its net utility, (i.e., utility minus cost) without considering other mobiles. The performance of their algorithm depends on the choice of the price. However, they do not provide a strategy for determining the optimal price.

In this paper, we jointly study the resource allocation and base-station assignment problems for the downlink in CDMA networks. The resource allocation part of the problem includes optimizing over both power and rate allocation. In this case, in addition to allocating an appropriate power level, we also need to determine an appropriate data rate for each mobile to improve system efficiency. In this paper, we allow for constraints on the maximum transmission power at the base-station and the maximum data rate for each mobile. It turns out that this problem is a nonconvex optimization problem. In general, obtaining an

Manuscript received January 27, 2003; revised October 22, 2003, May 25, 2004, October 25, 2004, and December 31, 2004; approved by IEEE/ACM TRANSACTIONS ON NETWORKING Editor M. Zukerman. This work was supported in part by the National Science Foundation under Grants ANI-0073359, ANI-9805441, and ANI-0207728. This research was conducted when J.-W. Lee and R. R. Mazumdar were at Purdue University.

J.-W. Lee is with the CITY-Center for Information Technology of Yonsei University, Department of Electrical and Electronic Engineering, Yonsei University, Seoul 120-749, Korea (e-mail: jangwon@yonsei.ac.kr).

R. R. Mazumdar is with the Department of Electrical and Computer Engineering, University of Waterloo, West Waterloo, ON, N2L 3G1 Canada (e-mail: mazum@ece.uwaterloo.ca).

N. B. Shroff is with the School of Electrical and Computer Engineering, Purdue University, West Lafayette, IN 47907 USA (e-mail: shroff@ecn.purdue.edu).

Digital Object Identifier 10.1109/TNET.2005.863480

optimal solution to a nonconvex optimization problem would require a very complex algorithm. Hence, in this paper, we focus on developing a simple distributed power and rate allocation algorithm. Even though this algorithm cannot guarantee to obtain the optimal solution, we will later show that the performance difference between our solution and the optimal solution is bounded by the performance of one mobile. Hence, the normalized error is $O(1/M)$, where M is the number of mobiles and, thus, this algorithm results in an asymptotically (in the number of mobiles) optimal power and rate allocation.

We next consider the base-station assignment problem in a multi-cellular system. In this work, a base-station is assigned to a mobile taking into account the congestion level of the cell as well as the transmission environment of the mobile. To measure the congestion level of the cell and the transmission environment of the mobile, we use information from the joint power and rate allocation algorithm developed in this paper. Unlike the base-station assignment algorithms developed in [5]–[7] that are based on the uplink, our algorithm is based on downlink performance. In wireless networks, the downlink could be a bottleneck link because of the asymmetric bandwidth demand between the downlink and the uplink for data services [9]–[12]. Thus, it may be more appropriate to do base-station assignment based on the downlink performance. As shown in [13], for the joint power allocation and base-station assignment problems, the algorithm for the uplink cannot be easily modified for the use in the downlink, which necessitates studying the downlink problem independently.

In this paper, we also investigate how power and rates can be efficiently allocated in our system. As mentioned earlier, it has been shown that, for the downlink in an idealized system in which there is no constraint on the maximum data rate for each mobile, the optimal multiple access strategy is a TDMA type of strategy, i.e., selecting only one mobile at a time and transmitting to it at the maximum transmission power. In addition, it can be easily shown that if all mobiles are homogeneous, selecting a mobile in the best transmission environment is an optimal mobile selection strategy. However, in practice, due to either the physical limitation of the hardware or limits of the individual applications, the maximum data rate for each mobile is bounded. Further, each mobile could have a different transmission scheme (e.g., a different modulation or coding scheme) that depends on the channel condition and the application [14]. This results in the mobiles being heterogeneous. In this paper, we study the properties of efficient multiple access and mobile selection strategies taking into account these two practically important generalizations (heterogeneity and maximum data rate constraints) and show that *a strategy that transmits to only one mobile in the best transmission environment at a time may not be optimal*.

To develop a power and rate allocation algorithm, we will use a few basic theoretical results from our previous papers [15], [16], in which we focused on theoretically solving a nonconvex optimization problem. However, compared to our previous works [15], [16], this paper has the following distinguishing features. First, in this paper, we study a joint power and rate allocation problem in the system allowing for *variable* data rates, while in [15] and [16], only a power allocation problem with a fixed data rate was studied. This is important since most next generation wireless systems are expected to support variable data rates [14], [17]. Further, in this paper, we study the effects of various factors (e.g., the maximum data rate, the transmission scheme, and the transmission environment) on the resource allocation strategies (e.g., the optimal data rate, the multiple access strategy, and the mobile selection strategy), which provide insight into the development of efficient resource allocation strategies. Finally, in this paper, we also study a base-station assignment problem that considers a multi-cellular system, in contrast to the single cell system that was studied in [15] and [16].

The rest of the paper is organized as follows. In Section II, we describe the system model. We present the joint power and rate allocation algorithm in Section III and study the properties of power and rate allocation in Section IV. In Section V, the base-station assignment algorithm is presented. We provide numerical results using computer simulation in Section VI and conclude in Section VII.

II. System Model

We focus on the downlink in a CDMA network. The network consists of B base-stations (cells) and M mobiles. The system is assumed to be time-slotted. A time slot in our system is an arbitrary interval of time and could consist of one or several packets. We assume that the path gain, background noise, and intercell interference for each mobile are fixed during the time slot [18]. At the beginning of each time slot, power and rate allocation for each mobile in the current time slot is obtained by executing the power and data rate allocation algorithm. Based on that, the base-station for the next time slot is assigned to each mobile by executing the base-station assignment algorithm. Each base-station has a maximum power limit P_T and each mobile communicates with one base-station. For a given mobile i, $R_i^{\max}$ is the maximum rate at which it can receive data. Further, f_i is a function for the probability of a successful packet transmission for mobile i, and is a function of $\gamma_i \triangleq E_b/I_0$ (bit energy to interference density ratio). For a mobile i that communicates with base-station h, we can express γ_i as [3], [4]

$$\begin{aligned}\gamma_i\left(R_i, \bar{P}(h)\right) &= \frac{W}{R_i}\frac{G_i(h)P_i}{\theta G_i(h)\sum\limits_{m\in M(h)} P_m - \theta G_i(h)P_i + I_i(h)} \\ &= \frac{W}{R_i}\frac{P_i}{\theta \sum\limits_{m\in M(h)} P_m - \theta P_i + A_i(h)},\end{aligned}$$

where

W	chip rate;
θ	orthogonality factor;
$M(h)$	set of mobiles that communicate with base-station h;
P_i	power allocation for mobile i;
R_i	data rate for mobile i;
$\bar{P}(h)$	power allocation vector for mobiles that communicate with base-station h;
$G_i(h)$	path gain from base-station h to mobile i;

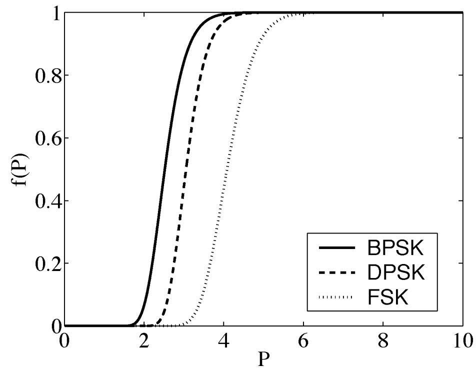

Fig. 1. Probabilities of a successful packet transmission for BPSK, DPSK, and FSK modulation schemes.

$I_i(h)$ background noise and intercell interference to mobile i that communicates with base-station h;

$A_i(h)$ $\triangleq I_i(h)/G_i(h)$transmission environment between mobile i and base-station h.

The function for the probability of a successful packet transmission, f_i, depends on the various transmission (modulation and coding) schemes being used. In this paper, we do not assume that any specific transmission scheme is used for communication. However, we assume that f_i has the following properties.

Assumptions:

(a) f_i is an increasing function of γ_i.

(b) f_i is twice continuously differentiable.

(c) $f_i(0) = 0$.

(d) $(\partial^2 f_i(\gamma_i)/\partial\gamma_i^2)((W/R_i^{\max}) + \theta\gamma_i) + 2\theta(\partial f_i(\gamma_i)/\partial\gamma_i) = 0$ has at most one solution for $\gamma_i > 0$.

(e) If $(\partial^2 f_i(\gamma_i)/\partial\gamma_i^2)((W/R_i^{\max}) + \theta\gamma_i) + 2\theta(\partial f_i(\gamma_i)/\partial\gamma_i) = 0$ has one solution at $\gamma_i^o > 0$, $(\partial^2 f_i(\gamma_i)/\partial\gamma_i^2)((W/R_i^{\max}) + \theta\gamma_i) + 2\theta(\partial f_i(\gamma_i)/\partial\gamma_i) > 0$ for $\gamma_i < \gamma_i^o$ and $(\partial^2 f_i(\gamma_i)/\partial\gamma_i^2)((W/R_i^{\max}) + \theta\gamma_i) + 2\theta(\partial f_i(\gamma_i)/\partial\gamma_i) < 0$ for $\gamma_i > \gamma_i^o$.

Remark 1: By the assumptions above, if $\sum_{i\in M(h)} P_i = P_T$, then at the maximum data rate, $R_i^{\max}$, f_i can be one of three types: a sigmoidal-like function,[1] a concave function, or a convex function of its own power allocation (see Lemma 2 in [15]). We will show in Proposition 1 that $\sum_{i\in M(h)} P_i = P_T$, if the system is operating at maximum throughput. In most cases, the function for the probability of a successful packet transmission at a fixed data rate can be characterized by one of these three types of functions, as shown in Fig. 1. In this figure, we provide examples for various modulation schemes such as binary phase-shift keying (BPSK), differential phase-shift keying (DPSK), and frequency-shift keying (FSK) [19]. We assume that a packet consists of 800 bits without channel coding and set $P_T = 10$, $\theta = 1$, $(W/R_i) = 16$, and $A_i(h) = 0.7407$. In this figure, the function for the probability of a successful packet transmission for each modulation scheme is represented by a sigmoidal-like function of its power allocation.

[1]A sigmoidal-like function means a function $f_i(x)$ that has one inflection point, x^o and $(d^2 f_i(x)/dx^2) > 0$ for $x < x^o$ and $(d^2 f_i(x)/dx^2) < 0$ for $x > x^o$, i.e., $f_i(x)$ is a convex function for $x < x^o$ and a concave function for $x > x^o$.

III. Power and Rate Allocation

In this section, we study the power and data rate allocation problem by focusing on one cell of the system. Hence, for notational convenience, in this section, we will omit the parameter denoting the base-station. At the beginning of each time slot, the power and rate allocation algorithm is executed to obtain the power and rate allocation for that time slot. We focus on a time slot assuming that the path gain, background noise, and intercell interference for each mobile are fixed. We assume that mobiles from 1 to M communicate with the base-station. Each mobile i has a utility function, U_i, which is defined to be its expected throughput as

$$U_i(R_i, \bar{P}) = R_i f_i\left(\gamma_i(R_i, \bar{P})\right), \quad i = 1, 2, \ldots, M. \tag{1}$$

Then, the optimization problem for power and rate allocation considered in this paper is given by

$$\begin{aligned}
\text{(A)} \quad & \max_{\bar{P},\bar{R}} \sum_{i=1}^{M} U_i(R_i, \bar{P}) \\
& \text{subject to} \quad \sum_{i=1}^{M} P_i \le P_T, \\
& \qquad 0 \le P_i \le P_T, \quad i = 1, 2, \ldots, M, \\
& \qquad 0 \le R_i \le R_i^{\max}, \quad i = 1, 2, \ldots, M,
\end{aligned}$$

where $\bar{P} = (P_1, P_2, \ldots, P_M)$ and $\bar{R} = (R_1, R_2, \ldots, R_M)$. Therefore, our goal is to *maximize the total expected system throughput (the total system utility)* with constraints on the maximum transmission power at the base-station and the maximum data rate for each mobile.

A. Optimal Rate Allocation for a Given Power Allocation

To solve problem (A), we first calculate the optimal data rate for a given power allocation. To this end, we provide the following proposition.

Proposition 1: A necessary condition to achieve maximum system throughput is that the base-station must transmit at its maximum power level P_T.

Proof: See Appendix I. ■

Hence, from now on, we will assume that $\sum_{i=1}^{M} P_i = P_T$. This allows us to rewrite $\gamma_i(R_i, \bar{P})$ as a function of only R_i and P_i as shown below.

$$\begin{aligned}
\gamma_i(R_i, \bar{P}) &= \frac{W}{R_i} \frac{P_i}{\theta \sum_{m=1}^{M} P_m - \theta P_i + A_i} \\
&= \frac{W}{R_i} \frac{P_i}{\theta P_T - \theta P_i + A_i} \\
&\triangleq \gamma_i(R_i, P_i), \quad i = 1, 2, \ldots, M.
\end{aligned}$$

Hence, we can rewrite the expected throughput of mobile i defined in (1) as

$$U_i(R_i, P_i) = R_i f_i\left(\gamma_i(R_i, P_i)\right) \tag{2}$$

i.e., without dependence on the power allocation for the other mobiles. Therefore, as given by the following proposition, each mobile i can determine the optimal data rate $R_i^*(P_i)$ for a given power allocation P_i without considering the other mobiles.

Proposition 2: If $\sum_{i=1}^{M} P_i = P_T$, then for a given power allocation P_i, the optimal rate for mobile i, $R_i^*(P_i)$, is obtained as

$$R_i^*(P_i)=\begin{cases} \dfrac{WP_i}{\gamma_i^*(\theta P_T-\theta P_i+A_i)}, & \text{if } P_i \le \dfrac{R_i^{\max}\gamma_i^*(\theta P_T+A_i)}{W+\theta R_i^{\max}\gamma_i^*} \\ R_i^{\max}, & \text{otherwise} \end{cases}$$

where $\gamma_i^* = \arg\max_{\gamma\ge 1}\{(1/\gamma)f_i(\gamma)\}$.

Proof: See Appendix II. ■

Hence, the optimal rate of a mobile can be represented as a function of its power allocation. Using (2) and Proposition 2, the expected throughput of mobile i (at the optimal data rate allocation for a given power allocation, P_i) is expressed as[2]

$$U_i^{R_i^*}(P_i) \triangleq U_i\left(R_i^*(P_i), P_i\right) = \begin{cases} \dfrac{W}{\gamma_i^*}\dfrac{P_i}{\theta P_T - \theta P_i + A_i} f_i(\gamma_i^*), \\ \qquad \text{if } P_i \le \dfrac{R_i^{\max}\gamma_i^*(\theta P_T + A_i)}{W+\theta R_i^{\max}\gamma_i^*} \\ R_i^{\max} f_i\left(\gamma_i\left(R_i^{\max}, P_i\right)\right), \\ \qquad \text{otherwise} \end{cases} \quad (3)$$

and by using it, we now introduce a new optimization problem (B):

$$\text{(B)} \quad \max_{\bar{P}} \sum_{i=1}^{M} U_i^{R_i^*}(P_i)$$
$$\text{subject to} \quad \sum_{i=1}^{M} P_i \le P_T,$$
$$0 \le P_i \le P_T, \quad i = 1, 2, \ldots, M.$$

In problem (B), the original power and rate allocation problem is reduced to a power allocation problem. Hence, we can assume that each mobile i has its utility function $U_i^{R_i^*}(P_i)$ instead of the original utility function $U_i(R_i, P_i)$. Even though problems (A) and (B) are different from each other: one is a joint power and rate allocation problem and the other is a power allocation problem, we can obtain joint power and rate allocation that solves problem (A) by solving problem (B) and using Proposition 2. To this end, we first solve problem (B) with $U_i^{R_i^*}(P_i)$, $\forall i$ and obtain the appropriate power allocation for each mobile. Then, the optimal transmission data rate for each mobile can be obtained via Proposition 2 based on the power allocation.

Remark 2: In (3), $U_i^{R_i^*}(P_i)$ is a convex function for $P_i \le (R_i^{\max}\gamma_i^*(\theta P_T + A_i))/(W + \theta R_i^{\max}\gamma_i^*))$ and the shape of $U_i^{R_i^*}(P_i)$ follows the shape of f_i at $R_i^{\max}$ for $(R_i^{\max}\gamma_i^*(\theta P_T + A_i)/(W + \theta R_i^{\max}\gamma_i^*)) < P_i \le P_T$. Therefore, $U_i^{R_i^*}(P_i)$ is a convex function, or a sigmoidal-like function of P_i, since by the assumptions, f_i is either a convex function, a concave function, or a sigmoidal-like function of P_i at $R_i^{\max}$.

Remark 3: Since we assume that the base-station transmits at its maximum power level P_T, problem (B) should have $\sum_{i=1}^{M} P_i = P_T$ instead of $\sum_{i=1}^{M} P_i \le P_T$ in the constraint. However, because the sum of the power allocation must be P_T at the optimal solution to problem (B), it makes no difference to write the constraint as an inequality. Moreover, this allows us to use the algorithm that has been developed in [15] and [16] to obtain the appropriate power allocation.

Since $U_i^{R_i^*}$ could be a sigmoidal-like function, which is the more interesting case, in general, it is not easy to obtain an optimal solution for problem (B). However, it turns out that the structure of problem (B) is similar to that of the problem studied in [15] and [16]. In [15] and [16], an algorithm was developed to obtain an asymptotically optimal power allocation when the number of mobiles is large (i.e., $M \to \infty$). We can hence exploit the power allocation strategy in [15] and [16] to obtain an asymptotically optimal power allocation solution and then, obtain the optimal data rate for this power allocation by using Proposition 2. In the following, we briefly describe the power allocation algorithm. We refer readers to [15] and [16] for implementation and convergence issues of the algorithm.

B. Power Allocation

The power allocation algorithm is a pricing-based algorithm that is executed by each mobile and the base-station iteratively and in a distributed way. The basic idea of the algorithm is as follows. Based on the price $\lambda^{(n)}$ at iteration n, each mobile i requests a power allocation $P_i(\lambda^{(n)})$ (from the base-station) that maximizes its net utility, i.e.,

$$P_i\left(\lambda^{(n)}\right) = \arg\max_{0\le P\le P_T}\left\{U_i^{R_i^*}(P) - \lambda^{(n)}P\right\}. \quad (4)$$

Further, based on power requests from mobiles at iteration n, the base-station updates the price for the next iteration to find an appropriate price that provides an efficient power allocation. However, due to the nonconcavity of the utility function, it is not easy to find the price with a simple algorithm. Hence, the algorithm is divided into two stages: the mobile selection stage and the power allocation stage.

At the mobile selection stage, the base-station selects mobiles to which nonzero power are allocated. We next define a parameter $\lambda_i^{\max}$ that plays an important role in the mobile selection as

$$\lambda_i^{\max} = \min\left\{\lambda \ge 0 \middle| \max_{0\le P\le P_T}\left\{U_i^{R_i^*}(P) - \lambda P\right\} = 0\right\}.$$

We call $\lambda_i^{\max}$ the maximum willingness to pay of mobile i, since $P_i(\lambda) > 0$ for $\lambda \le \lambda_i^{\max}$ and $P_i(\lambda) = 0$ for $\lambda > \lambda_i^{\max}$. Each mobile i can calculate $\lambda_i^{\max}$ as

$$\lambda_i^{\max} = \begin{cases} \left.\dfrac{\partial U_i^{R_i^*}(P)}{\partial P}\right|_{P=P^*}, & \text{if } U_i^{R_i^*} \text{ is a sigmoidal-like function and } P^* \text{exists} \\ \dfrac{U_i^{R_i^*}(P_T)}{P_T}, & \text{otherwise} \end{cases} \quad (5)$$

[2]A mobile with the fixed data rate R_i^f can be easily accommodated in this problem, if we assume that $R_i^*(P_i) = R_i^f$ for $0 \le P_i \le P_T$.

where P^* is a unique solution of the following equation [15], [16]:

$$U_i^{R_i^*}(P) - P\frac{\partial U_i^{R_i^*}(P)}{\partial P} = 0, \quad P_i^o \le P \le P_T$$

and P_i^o is the inflection point of $U_i^{R_i^*}(P)$. Without loss of generality, we assume that $\lambda_1^{\max} \ge \lambda_2^{\max} \ge \cdots \ge \lambda_M^{\max}$. After calculating its maximum willingness to pay, each mobile reports it to the base-station. Then, the base-station broadcasts the prices, $\lambda_i^{\max}$, one by one in a decreasing order of $\lambda_i^{\max}$ to select mobiles from 1 to K satisfying

$$K = \max\left\{1 \le j \le M | \sum_{i=1}^{j} P_i\left(\lambda_j^{\max}\right) \le P_T\right\}. \quad (6)$$

Therefore, mobiles are selected in a decreasing order of their maximum willingness to pay.

At the power allocation stage, only those mobiles selected during the mobile selection stage solve (4) and request power based on the price from the base-station. Further, the base-station updates and broadcasts the price based on the power requests from the selected mobiles attempting to find an equilibrium price λ^* that satisfies

$$\sum_{i=1}^{K} P_i(\lambda^*) = P_T. \quad (7)$$

Note that there always exists such a unique λ^* and it can be obtained easily [15], [16]. Hence, power is allocated to the selected mobiles as $(P_1(\lambda^*), \ldots, P_K(\lambda^*))$. This power allocation is an optimal power allocation *for the selected set of mobiles*. However, since power is allocated to all mobiles as $(P_1(\lambda^*), \ldots, P_K(\lambda^*), 0, \ldots, 0)$, *it may not be an optimal power allocation for all mobiles*. We can show that if the condition

$$\sum_{i=1}^{K} P_i\left(\lambda_{K+1}^{\max}\right) < P_T \quad \text{and} \quad \sum_{i=1}^{K+1} P_i\left(\lambda_{K+1}^{\max}\right) > P_T \quad (8)$$

is not satisfied, the power allocation is an optimal power allocation for all mobiles, but if it is satisfied, we cannot guarantee that it is an optimal power allocation [16]. Nonetheless, the difference of the total system utilities between our power allocation and the upper bound on the optimal power allocation is bounded by the utility of one mobile [16]. Hence, the normalized error is $O(1/M)$ and, thus, *we can guarantee that it is always an asymptotically optimal power allocation for all mobiles* in the sense that if $\sum_{i=1}^{M} U_i^{R_i^o}(\gamma_i(P_i^o)) \to \infty$ as $M \to \infty$, then

$$\frac{\sum_{i=1}^{M} U_i^{R_i^*}\left(\gamma_i\left(P_i^*\right)\right)}{\sum_{i=1}^{M} U_i^{R_i^o}\left(\gamma_i\left(P_i^o\right)\right)} \to 1, \text{ as } M \to \infty$$

where $\bar{P}^o = (P_1^o, P_2^o, \ldots, P_M^o)$ and $\bar{R}^o = (R_1^o, R_2^o, \ldots, R_M^o)$ are optimal power and rate allocation, and $\bar{P}^* = (P_1^*, P_2^*, \ldots, P_M^*)$ and $\bar{R}^* = (R_1^*, R_2^*, \ldots, R_M^*)$ are our power and rate allocation. In [16], we have compared the performance of our power allocation and the upper bound when the number of mobiles is 10 and in most cases, our power allocation provides very close performance to the upper bound. Thus, the power allocation will be very close to the optimal power allocation for any realistic scenario when there are no highly asymmetrical mobiles.

IV. Study of the Proposed Power and Rate Allocation

In this section, we study the properties of the mobile selection strategy, the multiple access strategy, and the data rate allocation for the selected mobiles, which will provide insight into the development of overall efficient resource allocation strategies.

A. Study of the Mobile Selection Strategy

We first study the properties of the mobile selection strategy. Recall that A_i is defined by I_i/G_i, (where I_i is the background noise and intercell interference to mobile i, and G_i is the path gain from the base-station to mobile i), f_i is the function for the probability of a successful packet transmission for mobile i, and $R_i^{\max}$ is the maximum data rate for mobile i. Thus, A_i represents the degree of "goodness" of the transmission environment from the base-station to mobile i. That is a smaller value of A_i implies a better transmission environment.

We first define the efficiency of the mobile.

Definition 1: Mobile i is said to be more *efficient* than mobile j if $U_i^{R_i^*}(P) \ge U_j^{R_j^*}(P)$ for $0 \le P \le P_T$.

The next proposition shows the relationship between the mobile selection strategy and the efficiency of the mobile. Further, following the proposition are corollaries that show the relationship between the mobile selection strategy and the parameters of mobiles such as the maximum data rate, the transmission scheme, and the transmission environment.

Proposition 3: If mobile i is more efficient than mobile j, then $\lambda_i^{\max} \ge \lambda_j^{\max}$.

Proof: See Appendix III. ■

Proposition 3 asserts that if mobile i is more efficient than mobile j, mobile i has a greater chance to be selected by the algorithm than mobile j. This is the case because in the mobile selection algorithm, mobiles are selected in a decreasing order of $\lambda_i^{\max}$.

Corollary 1: Suppose $f_i(\gamma) = f_j(\gamma)$ and $A_i = A_j$. Then, if $R_i^{\max} > R_j^{\max}$, $\lambda_i^{\max} \ge \lambda_j^{\max}$.

Proof: See Appendix IV. ■

Corollary 1 implies that if the other conditions are same, the mobile with a higher maximum data rate has a higher priority to be selected than the mobile with a lower maximum data rate. Corollaries 2 and 3 can be proved in much the same way as Corollary 1.

Corollary 2: Suppose $R_i^{\max} = R_j^{\max}$ and $A_i = A_j$. Then, if $f_i(\gamma) \ge f_j(\gamma)$ for all γ, $\lambda_i^{\max} \ge \lambda_j^{\max}$.

In Corollary 2, $f_i(\gamma) \ge f_j(\gamma)$ implies that mobile i can achieve a higher probability of a successful packet transmission than mobile j with the same value of E_b/I_0, i.e., mobile i has a more efficient transmission scheme than mobile j. Hence, Corollary 2 implies that if the other conditions are same, the mobile with a more efficient transmission scheme has a higher priority to be selected than the mobile with a less efficient transmission scheme.

Corollary 3: Suppose $f_i(\gamma) = f_j(\gamma)$ and $R_i^{\max} = R_j^{\max}$. Then, if $A_i < A_j$, $\lambda_i^{\max} \geq \lambda_j^{\max}$.

Since $A_i < A_j$ implies that mobile i is in a better transmission environment than mobile j, if the other conditions are the same, Corollary 3 implies that a mobile in a better transmission environment has a higher priority to be selected than a mobile in a worse transmission environment. This also implies that if all mobiles are homogeneous, then mobiles are selected according to the transmission environment of each mobile, which is a well-known optimal mobile selection strategy for homogeneous mobiles [1].

It can easily be shown that the results in this subsection can be applied to the optimal power and rate allocation. Therefore, in the system with heterogeneous mobiles, the mobile selection strategy depends not only on the transmission environment of the mobiles but also on the other parameters such as the maximum data rate and the transmission scheme of mobiles. This implies that, in general situations in which several conditions are mixed, it is not easy to determine which mobiles must be selected for the optimal solution. However, our mobile selection provides a simple and unified strategy of mobile selection among heterogeneous mobiles, while providing a good approximation of the optimal solution by giving a higher priority to be selected to a more efficient mobile.

B. Study of the Multiple Access Strategy

In this subsection, we study the optimality conditions of a TDMA type of multiple access that transmits to only one mobile at a time and a CDMA type of multiple access that transmits to all mobiles simultaneously. The next proposition gives us optimality conditions for both these types of multiple access schemes.

Proposition 4:

(a) If $P_1(\lambda_2^{\max}) \geq P_T$, where $\lambda_1^{\max} > \lambda_2^{\max} > \cdots > \lambda_M^{\max}$, then a TDMA type of multiple access is an optimal strategy.

(b) If $\sum_{i=1}^{M} P_i(\lambda_M^{\max}) \leq P_T$, where $\lambda_1^{\max} > \lambda_2^{\max} > \cdots > \lambda_M^{\max}$, then a CDMA type of multiple access is an optimal strategy.

Proof: See Appendix V. ■

Corollary 4: If $R_i^{\max} A_i \geq (P_T W / \gamma_i^*)$ for all mobiles then a TDMA type of multiple access is optimal.

Proof: See Appendix VI. ■

Corollary 4 implies that if mobiles have a high enough maximum data rate or experience a poor transmission environment due to high interference or high channel loss, a TDMA type of multiple access is optimal. This also implies that if there is no constraint on the maximum data rate for mobiles, then the TDMA type of multiple access is always optimal, regardless of the transmission environment of mobiles as shown in [3], [4]. However, note that in general, the optimality conditions in Proposition 4 and Corollary 4 depend not only on system parameters that are constant, but also on the transmission environment of each mobile (time varying and location dependent), and the maximum data rate and the transmission scheme of each mobile (also time varying from the point of view of the system). Moreover, selecting a subset of mobiles at a time and transmitting only to them can be an optimal strategy depending on the system status. This suggests that a static strategy for multiple access could be inefficient in some cases and to obtain high system efficiency, we need a strategy that can be adapted to the dynamic characteristics of the system, such as the scheme developed in this paper.

C. Study of the Data Rate Allocation for the Selected Mobiles

In this subsection, we study the data rate allocation for the selected mobiles.

Proposition 5: Suppose that mobile i is selected by the mobile selection algorithm, then the transmission data rate for mobile i, R_i^*, is given by

$$R_i^* = \begin{cases} \dfrac{P_T W}{\gamma_i^* A_i} < R_i^{\max}, & \text{if } A_i > \dfrac{P_T W}{R_i^{\max} \gamma_i^*} \\ R_i^{\max}, & \text{otherwise.} \end{cases}$$

Proof: See Appendix VII. ■

In Proposition 5, R_i^* does not depend on the individual power level P_i. This is true even though the optimal data rate of a mobile is a function of the level of the power allocation, as shown in Proposition 2. The reason is that, from the proof of Proposition 5, if mobile i is selected, it is always allocated its maximum data rate, $R_i^{\max}$ or the total transmission power, P_T. With this property, the next corollary follows immediately.

Corollary 5: If multiple mobiles are selected simultaneously for transmission, each selected mobile is allocated its maximum data rate.

Corollary 5 implies that if the system is in the condition that multiple mobiles can be selected simultaneously for transmission (i.e., the optimality condition for the TDMA type of multiple access is not satisfied), all selected mobiles are always allocated their maximum data rate, even though they have variable data rates. A similar result can be shown for the optimal power and rate allocation.

Proposition 6: At the optimal power and rate allocation, at most one mobile among the selected mobiles for transmission is allocated the data rate that is less than its maximum data rate.

Proof: See Appendix VIII. ■

Hence, if the system is in the condition that multiple mobiles can be selected simultaneously for transmission in most cases, we may assume that each mobile has its maximum data rate as a fixed data rate, which makes resource allocation simple while preserving high system efficiency.

V. Base-Station Assignment

In the previous sections, we considered the joint power and rate allocation problem by focusing on one cell of the system. In this section, we now consider a multi-cellular system that brings with it two additional problems that were not considered in the previous sections. One is the total transmission power allocation problem for each base-station and the other is the base-station assignment problem for each mobile.

To maximize system performance, the resource allocation in a multi-cellular system must consider the status of each cell and the channel condition of each mobile. But, in practice, this would require a highly complex resource allocation algorithm, since it needs cooperation among base-stations. In addition, each base-station may require information not only from mobiles in its cell, but also from mobiles in other cells, resulting in a significant amount of signaling cost. For instance, Oh *et al.* extend their power control and spreading gain allocation algorithm for a single cell system [1] to a multi-cellular system [2]. To execute the algorithm, each base-station needs to know the information of the status of the mobiles in adjacent cells as well as its own cell. However, even with this significant amount of information, the algorithm is not guaranteed to converge to the optimal allocation and requires much longer convergence time than the algorithm for the single cell system.

In this paper, we adopt a strategy that each base-station tries to maximize its total system utility without considering the status of other cells. Using this strategy, each base-station executes the power and rate allocation algorithm in the previous section by independently transmitting at its maximum power level, thus making the algorithm simple. This is typically called a noncooperative situation and results in a Nash equilibrium operating point, which could be inefficient. If the load of each cell is unbalanced, the inefficiency might be large. To cope with this situation, we develop a base-station assignment algorithm. By reassigning some of the mobiles in the heavily loaded cells to lightly loaded cells, we expect to improve the total system utility by balancing the load among the base-stations. We next describe the base-station assignment algorithm.

At the beginning of each time slot, the base-stations independently execute the power and rate allocation algorithm in the previous section. For the base-station assignment part, we use the results of the power and rate allocation algorithm, which is a pricing-based algorithm. Thus, we call our base-station assignment the *pricing-based base-station assignment*. We first define the following variables:

- $\lambda_i^{\max}(h,t)$: maximum willingness to pay per unit power of mobile i for base-station h at time slot t;
- $\lambda^*(h,t)$: equilibrium price per unit power at base-station h at time slot t;
- $A_i(h,t)$: transmission environment between base-station h and mobile i at time slot t;
- $d_i(t)$: base-station that is assigned to mobile i a time slot t.

Assume that mobile i is communicating to base-station h, i.e., $d_i(t)=h$ at time slot t. If mobile i is selected for transmission by base-station h, it continues to communicate to base-station h during the next time slot, i.e., $d_i(t+1)=h$. But, if mobile i is not selected for transmission by base-station h, during the next time slot, it selects and connects to some base-station $d_i(t+1)$ that satisfies

$$d_i(t+1)=\arg\max_{k\in B_i(h,t)}\{\lambda_i^{\max}(k,t)-\lambda^*(k,t)\} \qquad (9)$$

where $B_i(h,t)$ is a set of candidate base-stations that can be assigned to the mobile during the next time slot. Note that $B_i(h,t)$ may not be the set of all base-stations. For example, $B_i(h,t)$ could be the set of base-stations adjacent to base-station h or the set of base-stations from which mobile i receives pilot signal with enough strength at time slot t.

We can explain the intuition of the algorithm using two interpretations. First, from the point of view of pricing, $\lambda_i^{\max}(h,t)$ can be interpreted as the maximum value per unit power of mobile i at base-station h at time slot t and $\lambda^*(h,t)$ can be interpreted as the current price per unit power at base-station h at time slot t. This implies that the value of $\lambda_i^{\max}(h,t)-\lambda^*(h,t)$ can be interpreted as the profit per unit power that mobile i can obtain if it is selected by base-station h at time slot t. Therefore, by solving (9), the mobile selects the base-station that may give it the highest profit per unit power in the next time slot based on information in the current time slot.

Another interpretation follows from the next two propositions.

Proposition 7: If $\lambda_i^{\max}(n,t)<\lambda_i^{\max}(m,t)$, then $A_i(n,t)>A_i(m,t)$.

Proof: See Appendix IX. ■

By the definition of $A_i(h,t)$, $\lambda_i^{\max}(n,t) < \lambda_i^{\max}(m,t)$ implies that the transmission environment between base-station m and mobile i is better than the transmission environment between base-station n and mobile i at time slot t. Hence, $\lambda_i^{\max}(h,t)$ is an indicator of the transmission environment between base-station h and mobile i at time slot t.

Proposition 8: Suppose that mobile i is selected by base-station n and mobile j is selected by base-station m at time slot t. Further suppose that $f_i=f_j$, $R_i^{\max}=R_j^{\max}$, and $A_i(n,t)=A_j(m,t)$. Then, if $\lambda_i^*(n,t)<\lambda_j^*(m,t)$, $P_i(\lambda^*(n,t))\geq P_j(\lambda^*(m,t))$.

Proof: See Appendix X. ■

Proposition 8 indicates that the base-station with a lower equilibrium price has less demand for power than the base-station with a higher equilibrium price, since a mobile is allocated more power from the former than the latter. Thus, we can interpret $\lambda^*(h,t)$ as being the *congestion level* at base-station h at time slot t. Hence, the value of $\lambda_i^{\max}(h,t)-\lambda^*(h,t)$ in (9) can be interpreted as the relative "goodness" of the transmission environment between mobile i and base-station h at time slot t, taking into account the congestion within the cell. From this interpretation, by solving (9), mobile i is reassigned to that base-station $d_i(t+1)$ in the next time slot, which may have the relatively best transmission environment (after considering the congestion within of the cell) in the next time slot among the candidate base-stations based on the information in the current time slot.

For the base-station assignment algorithm in (9), mobile i must calculate $\lambda_i^{\max}(k,t)$ and know $\lambda^*(k,t)$ for base-station $k\in B_i(h,t)$. Mobile i can calculate $\lambda_i^{\max}(k,t)$, if it knows $A_i(k,t)$ and P_T, and $A_i(k,t)$ can be measured at mobile i. Hence, the information that mobile i needs for the algorithm are P_T and $\lambda^*(k,t)$ for $k\in B_i(h,t)$ and these parameters must be transmitted from each base-station. They are base-station-specific parameters not mobile-specific parameters and they can be broadcasted by each base-station without requiring significant additional signaling cost for base-station assignment.

Note that our base-station assignment algorithm may not converge to the optimal base-station assignment. To obtain the optimal solution, we may need a complex algorithm that requires much more coordination between base-stations and mobiles. Hence, instead, we have developed a simple and distributed algorithm in which the base-station is assigned to the mobile based on pricing that reflects the congestion level of the base-

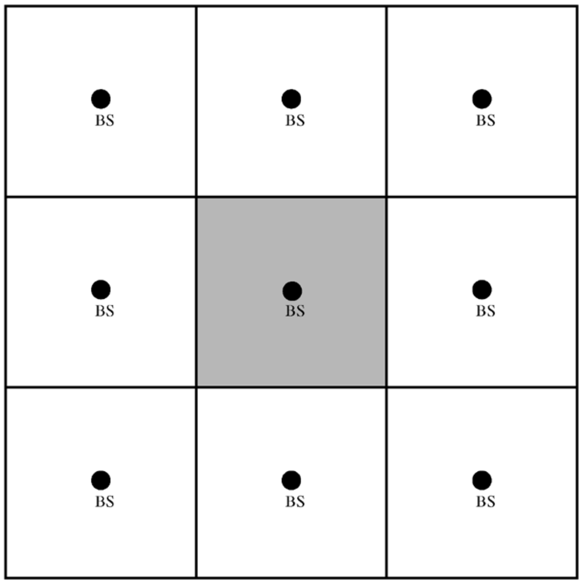

Fig. 2. Cellular network model.

TABLE I
PARAMETERS FOR THE SYSTEM

Maximum power (P_T)	10
Chip rate (W)	100000
Distance loss exponent (α)	4
Variance of log-normal distribution (σ^2)	8
Length of the side of the cell	1000

station as well as the transmission environment of the mobile. Even though our algorithm may not be optimal, as we will show in the next section, it provides more efficient base-station assignment than the conventional SINR-based algorithm in which the base-station is assigned to the mobile only based on the transmission environment of the mobile without considering the congestion level of the base-station.

VI. NUMERICAL RESULTS

In this section, we provide numerical results demonstrating the effectiveness of our power and rate allocation algorithm, and base-station assignment algorithm. We consider a cellular network with nine square cells as shown in Fig. 2. We assume that a base-station is located at the center of each cell. We model the path gain from base-station i to mobile j, $G_{i,j}$, as

$$G_{i,j} = \frac{K_{i,j}}{d_{i,j}^{\alpha}} \tag{10}$$

where $d_{i,j}$ is the distance from the base-station i to mobile j, α is a distance loss exponent, and $K_{i,j}$ is the log-normally distributed random variable with mean 0 and variance σ^2 (dB), which represents shadowing [20]. The parameters for the system are summarized in Table I. For the simulation, we use a sigmoid function to represent $f_i(\gamma)$, which is expressed as

$$f_i(\gamma) = c_i \left\{ \frac{1}{1 + e^{-a_i(\gamma - b_i)}} - d_i \right\} \tag{11}$$

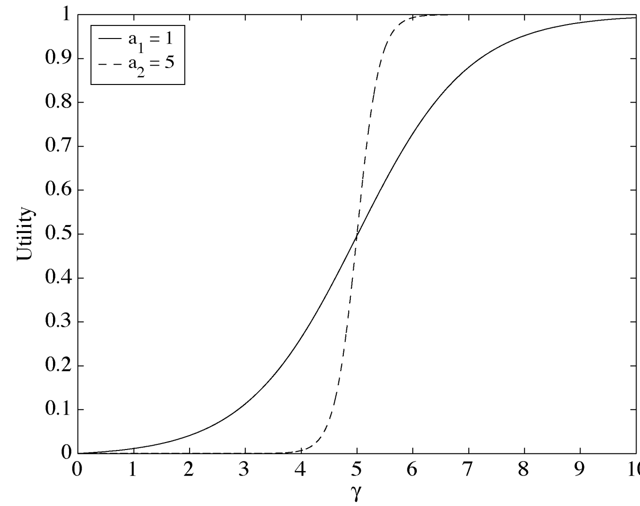

Fig. 3. Sigmoid functions with different a_i ($b_i = 5$).

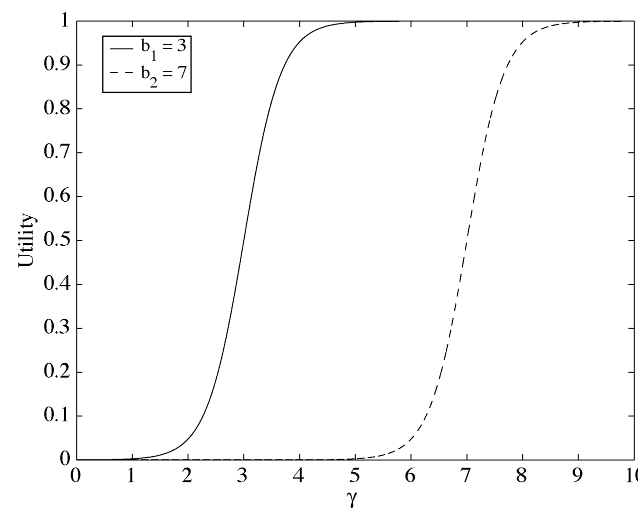

Fig. 4. Sigmoid functions with different b_i ($a_i = 3$).

where we set $c_i = (1 + e^{a_i b_i})/e^{a_i b_i}$ and $d_i = 1/(1 + e^{a_i b_i})$ for the normalization. The sigmoid utility functions with different values for a_i and b_i are provided in Figs. 3 and 4, respectively.

A. Power and Rate Allocation

We first present the performance of the power and rate allocation algorithm without considering base-station assignment. We focus on the cell at the center of the system and assume that all base-stations transmit at the maximum power limit. We also compare the performance of our algorithm with that of a TDMA type of multiple access, which is an optimal strategy when there is no constraint on the maximum data rate for each mobile [3], [4]. Such a strategy is also adopted in the IS-856 system (i.e., HDR) [8]–[10]. In this system, the downlink transmissions are time multiplexed and in each time slot, the base-station transmits to only one mobile. In the following, we call this scheme simply TDMA. To try to maximize the throughput of TDMA, we assume that the base-station transmits to a mobile that can achieve the highest expected throughput.

TABLE II
COMPARISON OF PERFORMANCES OF OUR POWER AND RATE ALLOCATION AND TDMA: TWO CLASSES WITH DIFFERENT MAXIMUM DATA RATES ($a_1 = a_2 = 3, b_1 = b_2 = 3.5$, AND $R_2^{\max} = 6250$)

R_1^{max}	1562.5	3125	6250	12500	25000
Selection ratio of class 1	0.501	0.428	0.388	0.348	0.198
Selection ratio of class 2	0.568	0.510	0.392	0.122	0.020
Utility (Our)/Utility (TDMA)	3.415	3.569	3.854	2.033	1.016

TABLE III
COMPARISON OF PERFORMANCES OF OUR POWER AND RATE ALLOCATION AND TDMA: TWO CLASSES WITH DIFFERENT FUNCTIONS FOR THE PROBABILITY OF A SUCCESSFUL PACKET TRANSMISSION ($a_1 = a_2 = 3$, $b_2 = 3.5$, AND $R_1^{\max} = R_2^{\max} = 6250$)

b_1	2.5	3.0	3.5	4.0	4.5
Selection ratio of class 1	0.566	0.472	0.391	0.306	0.230
Selection ratio of class 2	0.288	0.321	0.389	0.449	0.484
Utility (Our)/Utility (TDMA)	4.196	3.931	3.852	3.711	3.525

In Tables II and III, we assume that there are two classes of mobiles and set $\theta = 1$. A total of 10 mobiles are located independently according to a uniform distribution in the center cell and mobiles in each class are generated with probability 0.5.

In Table II, each class is assumed to have the same function for the probability of a successful packet transmission but a different maximum data rate. First, the selection ratio of mobiles for each class, which is defined as the ratio of the number of selected mobiles in the class to the number of mobiles in the class, is provided. The results indicate that the class with the higher maximum data rate has a higher selection ratio of mobiles than the class with the lower maximum data rate, as proved in Corollary 1. We also provide the ratio of the total system utility by our algorithm to that by TDMA. When $R_1^{\max} = 25\,000$, these two schemes give almost the same total system utility, because if there exist mobiles with high maximum data rates, TDMA is an optimal strategy, as shown in Corollary 4. However, when $R_1^{\max}$ is not too high, our power and rate allocation outperforms TDMA. This implies that, if $R_1^{\max}$ is not too high, the optimal strategy is to select multiple mobiles and transmit to them simultaneously and, thus, TDMA is optimized only for high data rate services. However, our algorithm can be used in any of the cases and results in high efficiency.

In Table III, each class has the same maximum data rate but a different function for the probability of a successful packet transmission (i.e., a different b_i). As shown in Fig. 4, a mobile with the lower value of b_i has a more efficient transmission scheme than a mobile with the higher value of b_i, since the former has a higher probability of a successful packet transmission than the latter at the same γ. Hence, the former has a higher priority to be selected than the latter, as proved in Corollary 2. The results also show that as the value of b_1 decreases, the performance difference between our power and rate allocation and TDMA gets larger. This implies that, as mobiles use more efficient transmission schemes, the base-station can select more mobiles and transmit to them simultaneously improving the system throughput.

In Table IV, we assume that each class has the same maximum data rate and the same function for the probability of a successful packet transmission. But we divide the cell into two regions: an inner region that is a square at the center of the cell whose length of the side is a half of that of the cell and an outer region that is the remaining region of the cell. We say that mobiles in the inner region belong to class 1 and mobiles in the outer region belong to class 2. Thus, in general, a mobile in class 1 is in a better transmission environment than a mobile in class 2. We set $\theta = 1$ and generate a total of 10 mobiles. We provide the results varying the ratio of the number of each class. As we studied in Corollary 3, the comparison of the selection ratio suggests that mobiles in a better transmission environment have a higher priority to be selected. The results also show that as the number of mobiles in a better transmission environment increases, the performance improvement of our scheme over TDMA also increases. Hence, as the number of mobiles in a better transmission environment increases, the base-station can transmit to more mobiles simultaneously, hence improving system efficiency.

TABLE IV
COMPARISON OF PERFORMANCES OF OUR POWER AND RATE ALLOCATION AND TDMA: TWO CLASSES WITH DIFFERENT TRANSMISSION ENVIRONMENTS ($R_1^{\max} = R_2^{\max} = 6250, a_1 = a_2 = 3$, AND $b_1 = b_2 = 3.5$)

Ratio of class 1	0.2	0.4	0.6	0.8
Selection ratio of class 1	0.981	0.849	0.653	0.499
Selection ratio of class 2	0.025	0.004	0	0
Utility (Our)/Utility (TDMA)	2.17031	3.40857	3.91211	3.98037

TABLE V
COMPARISON OF PERFORMANCES OF OUR POWER AND RATE ALLOCATION AND TDMA: SINGLE CLASS VARYING THE ORTHOGONALITY FACTOR ($R_1^{\max} = R_2^{\max} = 25\,000, a_1 = a_2 = 3$, AND $b_1 = b_2 = 3.5$)

θ	0.2	0.4	0.6	0.8	1.0
Utility (Our)/Utility (TDMA)	3.717	2.525	1.982	1.778	1

In Table V, we assume that a single class of mobiles are in the cell and provide the results varying θ, the orthogonality factor of the system. As we have a smaller orthogonality factor, mobiles have less intracell interference and the base-station can transmit to more mobiles simultaneously. This is indicated by the result that our scheme more outperforms TDMA, as the orthogonality factor gets smaller.

From the results thus far, we can infer that TDMA is an optimal multiple access strategy only for limited situations, while our algorithm can adapt to different situations providing high system efficiency.

B. Base-Station Assignment

We now present the performance of our base-station assignment algorithm. Recall that in our base-station assignment algorithm, power and rate are allocated using our power and rate allocation in the previous section. We call this *Algorithm A*. We also compare it with two other algorithms. One is called *Algorithm B*, in which power and rate are allocated using our power and rate allocation, but each mobile i is assigned to the base-station that satisfies

$$d_i(t+1) = \arg \min_{k \in B_i(h,t)} \{A_i(k,t)\}. \tag{12}$$

Hence, the mobile selects the base-station from which it can receive the highest SINR and we call this base-station assignment the *SINR-based base-station assignment*. This base-sta-

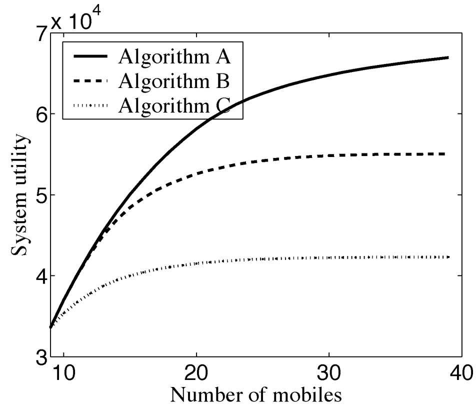

Fig. 5. System utility ($M_u = 1$).

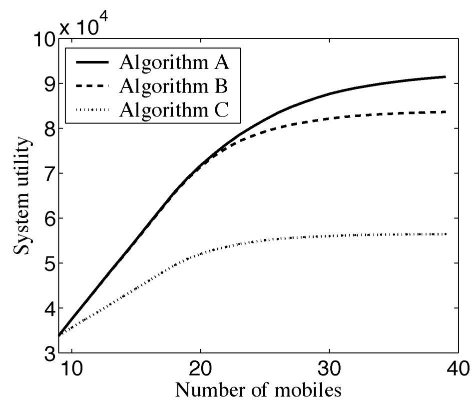

Fig. 6. System utility ($M_u = 2$).

tion assignment strategy is used in many practical systems including the IS-856 (HDR) system. The comparison of these two algorithms shows us the performance gain of the pricing-based base-station assignment algorithm over the SINR-based base-station assignment algorithm. The other algorithm is called *Algorithm C*, in which TDMA is used and each mobile is assigned to the base-station using (12). Hence, the multiple access and the base-station assignment schemes in *Algorithm C* are similar to those of the IS-856 (HDR) system. The comparison of *Algorithm C* and the other algorithms shows us that we can significantly improve system efficiency, if we take into account several resources jointly when developing resource allocation algorithms.

We assume that there are two classes of mobiles and set $a_1 = a_2 = 3$, $b_1 = b_2 = 3.5$, $R_1^{\max} = 12\,500$, and $R_2^{\max} = 1562.5$. Mobiles in class 1 are generated with probability 0.2 and mobiles in class 2 with probability 0.8. For the simulation, we model a hot-spot situation as follows. Up to $9 \times M_u$ mobiles, each mobile is generated in the system one by one in each cell in a sequential order, while trying to preserve a balanced load for each cell. After that, mobiles are generated in the center cell, while making a hot-spot situation. Hence, at the same number of mobiles, a smaller value of M_u indicates a higher degree of "unbalancedness" of the system. In addition, we assume that $\sigma^2 = 0$ in (10), which implies that at the SINR-based base-station assignment, each mobile is assigned to the closest base-station from it.

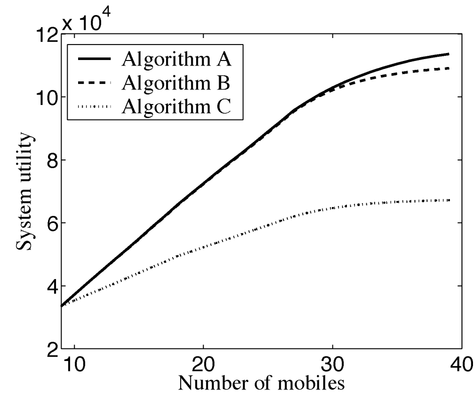

Fig. 7. System utility ($M_u = 3$).

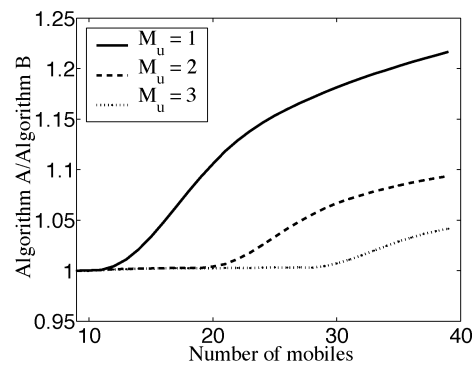

Fig. 8. Ratio of utility of Algorithm A to that of Algorithm B.

In Figs. 5–7, we compare the system utility achieved by each algorithm while varying M_u. In the way we generate mobiles, if the number of mobiles is less than or equal to 9, each base-station has at most one mobile, and, thus, all three algorithms provide the same results. The results show that *Algorithm A* outperforms *Algorithm B* during the hot-spot period. This implies that the pricing-based base-station assignment outperforms the SINR-based base-station assignment at the hot-spot situation, since the former can maintain load balancing among the base-stations by reassigning the mobiles in the more congested base-station to less congested base-stations. As shown in the single cell results, *Algorithm B* outperforms *Algorithm C*, and, thus, so does *Algorithm A*. In Fig. 8, we provide the ratio of the system utility achieved by *Algorithm A* to that achieved by *Algorithm B* for $M_u = 1, 2, 3$, respectively. Since, as the "unbalancedness" of the system increases (i.e., as M_u decreases), more mobiles in the hot-spot cell can be reassigned to the other cells, the performance gain of *Algorithm A* over *Algorithm B* also increases. The results also imply that balancing the load of each cell by connecting mobiles to the base-station considering the load of each cell and the channel condition is more beneficial in increasing the system utility than connecting the mobiles to the base-station with the best channel condition.

We compare the increment of the system utility during the hot-spot period in Figs. 9–11. In these figures, the increment in system utility is defined as the system utility achieved by all mobiles minus the system utility when only $9 \times M_u$ mobiles exist. The number of mobiles during the hot-spot period, M_h, means that the number of mobiles added at the center cell during the

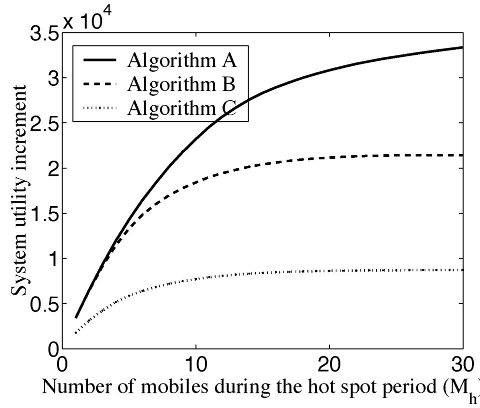

Fig. 9. System utility increment during the hot-spot period $(M_u = 1)$.

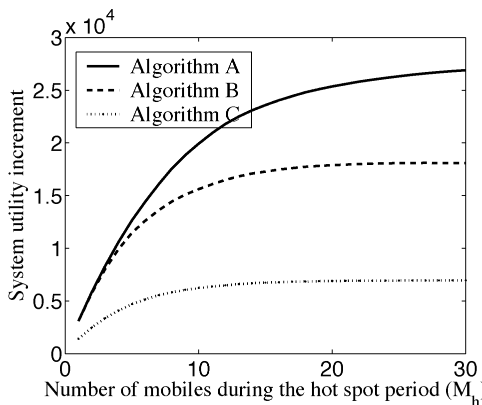

Fig. 10. System utility increment during the hot-spot period $(M_u = 2)$.

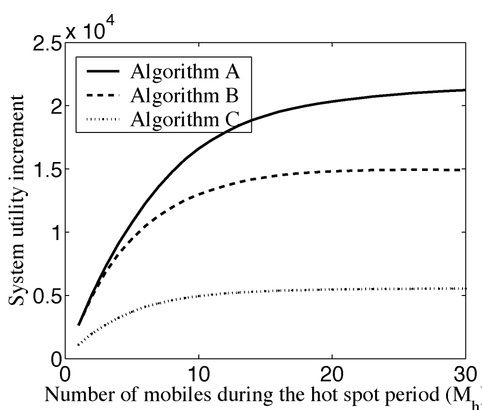

Fig. 11. System utility increment during the hot-spot period $(M_u = 3)$.

hot-spot period. As shown in the figures, *Algorithm A* gives the highest performance while *Algorithm C* gives the lowest performance.

In Fig. 12, the ratio of the increment in the utility of *Algorithm A* to that of *Algorithm B* is provided varying M_u, the degree of "unbalancedness" of the system. When M_h is small, the performance gain of *Algorithm A* over *Algorithm B* increases, as M_u increases. In such a case, the hot-spot cell with a smaller M_u is less congested and, thus, it has smaller performance gain. However, when the hot-spot cell is congested (i.e., M_h is large), the performance gain depends on the congestion level of adjacent

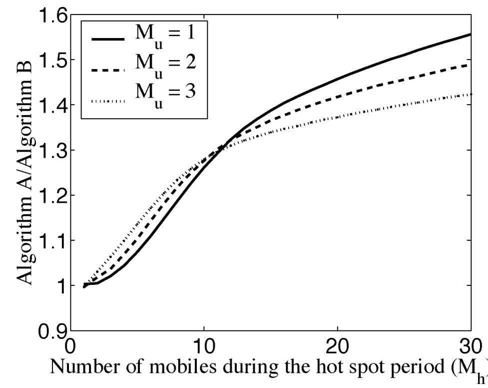

Fig. 12. Ratio of utility increment of Algorithm A to that of Algorithm B during the hot-spot period.

cells. As adjacent cells are less congested (i.e., smaller M_u), the number of mobiles that can be reassigned to adjacent cells increases and, thus, the performance gain increases. Thus, the results tell us that the performance gain of our base-station assignment algorithm over the SINR-based base-station assignment depends not only on the congestion level of the cell itself but also on the difference between the congestion levels among cells.

VII. Conclusion

In this paper, we have provided a concrete framework for developing efficient joint power and rate control schemes for CDMA networks. In particular, this framework clearly demonstrates the single-user scheduling with the best channel condition per time-slot, which is viewed as optimal currently, is only optimal in the absence of rate constraints and in the homogenous case. When there are rate constraints, single-user schemes can be sub-optimal and multiple-users must be served for system efficiency. This optimization framework furthermore provides the appropriate parameters for selecting the mobiles to be served in a time-slot, when users are heterogeneous.

The second issue that this paper addresses is the issue of base-station assignment. We have shown that the outcomes of our power and rate allocation algorithm can be used as measures of the channel condition as well as congestion at a base-station. This allows us to perform base-station assignment based both on channel conditions as well as congestion. We have shown that such a scheme outperforms one that is based on channel conditions alone and the performance of our algorithm improves as the loads on base-stations becomes more asymmetric.

Appendix I
Proof of Proposition 1

Let $\bar{P} = (P_1, P_2, \ldots, P_M)$ be a power allocation vector such that $\sum_{i=1}^{M} P_i < P_T$. Then, it suffices to show that there exists another power allocation $\bar{P}^* = (P_1^*, P_2^*, \ldots, P_M^*)$ such that $\sum_{i=1}^{M} P_i^* = P_T$ that improves the total system throughput.

If $\sum_{i=1}^{M} P_i < P_T$, then there exists an $m > 1$ such that

$$\sum_{i=1}^{M} P_i < m \sum_{i=1}^{M} P_i = P_T.$$

We define $P_i^* = mP_i$ for $i = 1, 2, \ldots, M$, then

$$\begin{aligned}\gamma_i(R_i, \bar{P}^*) &= \frac{W}{R_i} \frac{P_i^*}{\theta \sum_{j=1}^{M} P_j^* - \theta P_i^* + A_i} \\ &= \frac{W}{R_i} \frac{mP_i}{\theta \sum_{j=1}^{M} mP_j - \theta mP_i + A_i} \\ &> \frac{W}{R_i} \frac{mP_i}{\theta \sum_{j=1}^{M} mP_j - \theta mP_i + mA_i} \\ &= \gamma_i(R_i, \bar{P}), \quad i = 1, 2, \ldots, M.\end{aligned}$$

Therefore, $U_i(R_i, \gamma_i(R_i, \bar{P}^*)) > U_i(R_i, \gamma_i(R_i, \bar{P}))$ for all i, since U_i (i.e., f_i) is an increasing function of γ_i.

Appendix II
Proof of Proposition 2

First, suppose that $R_i^{\max} = \infty$, i.e., $N_i^{min} \triangleq W/R_i^{\max} = 0$. Then, by Proposition 1 in [1]

$$R_i^*(P_i) = \frac{WP_i}{\gamma_i^*(\theta P_T - \theta P_i + A_i)}$$

where $\gamma_i^* = \arg\max_{\gamma \geq 1}\{(1/\gamma) f_i(\gamma)\}$. In this paper, we have a constraint on the maximum data rate, $R_i^{\max}$. Therefore, considering the constraint

$$R_i^*(P_i) = \begin{cases} \dfrac{WP_i}{\gamma_i^*(\theta P_T - \theta P_i + A_i)}, & \text{if } \dfrac{WP_i}{\gamma_i^*(\theta P_T - \theta P_i + A_i)} \leq R_i^{\max} \\ R_i^{\max}, & \text{otherwise} \end{cases}$$

and the equation above is equivalent to

$$R_i^*(P_i) = \begin{cases} \dfrac{WP_i}{\gamma_i^*(\theta P_T - \theta P_i + A_i)}, & \text{if } P_i \leq \dfrac{R_i^{\max}\gamma_i^*(\theta P_T + A_i)}{W + \theta R_i^{\max}\gamma_i^*} \\ R_i^{\max}, & \text{otherwise.} \end{cases}$$

Appendix III
Proof of Proposition 3

Let us define

$$w_i(\lambda) = \max_{0 \leq P \leq P_T} \left\{ U_i^{R_i^*}(P) - \lambda P \right\},$$

and

$$w_j(\lambda) = \max_{0 \leq P \leq P_T} \left\{ U_j^{R_j^*}(P) - \lambda P \right\}.$$

Then, $w_i(\lambda) \geq w_j(\lambda)$, since we assume that mobile i is more efficient than mobile j, i.e., $U_i^{R_i^*}(P) \geq U_j^{R_j^*}(P)$ for $0 \leq P \leq P_T$. Further, by the definition of $\lambda_j^{\max}$

$$w_i\left(\lambda_j^{\max}\right) \geq w_j\left(\lambda_j^{\max}\right) = 0.$$

Hence

$$\lambda_i^{\max} \geq \lambda_j^{\max}$$

since we must have $w_i(\lambda_i^{\max}) = 0$ by the definition of $\lambda_i^{\max}$ and $w_i(\lambda)$ is a nonincreasing function of λ.

Appendix IV
Proof of Corollary 1

Since $A_i = A_j$, $\gamma_i(R, P) = \gamma_j(R, P)$ and

$$\begin{aligned}U_i^{R_i^*}(P) &= \max_{0 \leq R \leq R_i^{\max}} \{Rf_i(\gamma_i(R, P))\} \\ &\geq \max_{0 \leq R \leq R_j^{\max}} \{Rf_i(\gamma_i(R, P))\} \\ &= \max_{0 \leq R \leq R_j^{\max}} \{Rf_j(\gamma_j(R, P))\} \\ &= U_j^{R_j^*}(P), \quad 0 \leq P \leq P_T.\end{aligned}$$

Therefore, mobile i is more efficient than mobile j and by Proposition 3, the proof is completed.

Appendix V
Proof of Proposition 4

We first prove Proposition 4(a). If $P_1(\lambda_2^{\max}) \geq P_T$, the condition in (8) is not satisfied and, thus, the power allocation is an optimal power allocation. Further, at the power allocation, by (6), only mobile 1 is selected, and by (7), the total transmission power is allocated to mobile 1.

Now, we prove Proposition 4(b). If $\sum_{i=1}^{M} P_i(\lambda_M^{\max}) \leq P_T$, the condition in (8) is not satisfied and, thus, the power allocation is an optimal power allocation. Further, at the power allocation, by (6), all mobiles are selected, and by (7), the total transmission power is allocated to all mobiles.

Appendix VI
Proof of Corollary 4

If $R_i^{\max} A_i \geq (P_T W/\gamma_i^*)$ for all mobiles, by a simple calculation, we can show that for each mobile i, $P_T \leq (r_i^{\max}\gamma_i^*(\theta P_T + A_i)/(W + \theta R_i^{\max}\gamma_i^*))$ and by (3), $U_i^{R_i^*}$ is a convex function. Hence, for each mobile i, by (5), $\lambda_i^{\max} = (U_i^{R_i^*}(P_T)/P_T)$ and by (4), $P_i(\lambda_i^{\max}) = P_T$. This satisfies the condition in Proposition 4(a).

Appendix VII
Proof of Proposition 5

Since we assume that mobile i selected, $P_i(\lambda^*) > 0$, where λ^* is an equilibrium price. Suppose $A_i > (P_T W/R_i^{\max}\gamma_i^*)$, then

$$P_T < \frac{R_i^{\max}\gamma_i^*(\theta P_T + A_i)}{W + \theta R_i^{\max}\gamma_i^*} \tag{13}$$

and by (3), $U_i^{R_i^*}(P_i)$ is a convex function for $0 \leq P_i \leq P_T$. By (5), mobile i has $\lambda_i^{\max} = (U_i^{R_i^*}(P_T)/P_T)$ and it has $P_i(\lambda) = 0$ for $\lambda > \lambda_i^{\max}$ and $P_i(\lambda) = P_T$ for $\lambda \leq \lambda_i^{\max}$. Since $P_i(\lambda^*) > 0$, mobile i is allocated power level P_T. Hence, by Proposition 2 and (13), $R_i^* = (P_T W/\gamma_i^* A_i)$ and $R_i^* < R_i^{\max}$. Now, suppose $A_i \leq (P_T W/R_i^{\max}\gamma_i^*)$, then

$$P_T \geq \frac{R_i^{\max}\gamma_i^*(\theta P_T + A_i)}{W + \theta R_i^{\max}\gamma_i^*}. \tag{14}$$

In this case, $U_i^{R_i^*}(P_i)$ is a convex function or a sigmoidal-link function for $0 \le P_i \le P_T$. If $U_i^{R_i^*}(P_i)$ is a convex function, mobile i is allocated power level P_T. Hence, by Proposition 2 and (14), $R_i^* = R_i^{\max}$. If $U_i^{R_i^*}(P_i)$ is a sigmoidal-like function, mobile i is allocated power level $P_i(\lambda^*)$ that forces $U_i^{R_i^*}(P_i(\lambda^*))$ to be in the concave region, since $P_i(\lambda) > 0$ that forces $U_i^{R_i^*}(P_i(\lambda))$ to be in the convex region does not satisfy the second order necessary condition for the solution of (4), $(\partial^2 U^{R_i^*}(P)/\partial P^2) < 0$. This implies that $P_i(\lambda^*) > (R_i^{\max}\gamma_i^*(\theta P_T + A_i)/(W + \theta R_i^{\max}\gamma_i^*))$, since $U_i^{R_i^*}(P_i)$ is a convex function for $P_i \le (R_i^{\max}\gamma_i^*(\theta P_T + A_i)/(W + \theta R_i^{\max}\gamma_i^*))$ by (3). Therefore, by Proposition 2, $R_i^* = R_i^{\max}$.

APPENDIX VIII
PROOF OF PROPOSITION 6

In the next lemma, we first show that at the optimal power and rate allocation, the marginal utilities of the selected mobiles are same.

Lemma 1: If $\bar{P}^* = (P_1^*, \ldots, P_M^*)$ is an optimal power allocation and K is the set of the selected mobiles for transmission, then $\partial U_i^{R_i^*}(P_i)/\partial P_i|_{P_i=P_i^*} = \partial U_j^{R_j^*}(P_j)/\partial P_j|_{P_j=P_j^*}$ for all i, $j \in K$.

Proof: We will prove this by using contradiction. Suppose that $\bar{P}^* = (P_1^*, \ldots, P_M^*)$ is an optimal power allocation, $P_i^* > 0$, $P_j^* > 0$, and $\partial U_i^{R_i^*}(P_i)/\partial P_i|_{P_i=P_i^*} > \partial U_j^{R_j^*}(P_j)/\partial P_j|_{P_j=P_j^*}$. Thus, we can find δP such that $\partial U_i^{R_i^*}(P_i)/\partial P_i > \partial U_j^{R_j^*}(P_j)/\partial P_j$ for all $P_i \in [P_i^*, P_i^* + \delta P]$ and $P_j \in [P_j^* - \delta P, P_j^*]$. Hence

$$\int_{P_i^*}^{P_i^*+\delta P} \frac{\partial U_i^{R_i^*}(P_i)}{\partial P_i} dp > \int_{P_j^*-\delta P}^{P_j^*} \frac{\partial U_j^{R_j^*}(P_j)}{\partial P_j} dp.$$

This implies that

$$U_i^{R_i^*}(P_i^* + \delta P) - U_i^{R_i^*}(P_i^*) > U_j^{R_j^*}(P_j^*) - U_j^{R_j^*}(P_j^* - \delta P)$$
$$U_i^{R_i^*}(P_i^* + \delta P) + U_j^{R_j^*}(P_j^* - \delta P) > U_i^{R_i^*}(P_i^*) + U_j^{R_j^*}(P_j^*)$$

and utilities for all other mobiles are unchanged, which gives the contradiction. ■

Now, we will prove Proposition 6. We first show by contradiction that at the optimal power allocation, at most one mobile among the selected mobiles for transmission achieves a utility value in the convex region of the utility function. Suppose that $\bar{P}^* = (P_1^*, \ldots, P_M^*)$ is an optimal power allocation, $P_i^* > 0$, $P_j^* > 0$, and $U_i^{R_i^*}(P_i^*)$ and $U_j^{R_j^*}(P_j^*)$ are in the convex region. Since P_i^* and P_j^* are optimal allocation, by Lemma 1

$$\left.\frac{\partial U_i^{R_i^*}(P_i)}{\partial P_i}\right|_{P_i=P_i^*} = \left.\frac{\partial U_j^{R_j^*}(P_j)}{\partial P_j}\right|_{P_j=P_j^*}$$

and we can find δP such that $U_i^{R_i^*}(P_i)|_{P_i=P_i^*+\delta P}$ and $U_j^{R_j^*}(P_j)|_{P_j=P_j^*-\delta P}$ are still in the convex region. Hence

$$\int_{P_i^*}^{P_i^*+\delta P} \frac{\partial U_i^{R_i^*}(P_i)}{\partial P_i} dp > \int_{P_j^*-\delta P}^{P_j^*} \frac{\partial U_j^{R_j^*}(P_j)}{\partial P_j} dp$$

since $\partial U_i^{R_i^*}(P_i)/\partial P_i$ and $\partial U_j^{R_j^*}(P_j)/\partial P_j$ are increasing functions of P_i and P_j, respectively. This implies that

$$U_i^{R_i^*}(P_i^* + \delta P) - U_i^{R_i^*}(P_i^*) > U_j^{R_j^*}(P_j^*) - U_j^{R_j^*}(P_j^* - \delta P)$$
$$U_i^{R_i^*}(P_i^* + \delta P) + U_j^{R_j^*}(P_j^* - \delta P) > U_i^{R_i^*}(P_i^*) + U_j^{R_j^*}(P_j^*)$$

and utilities for all other mobiles are unchanged, which is contradiction. Hence, at most one mobile among the selected mobiles for transmission achieves utility value in the convex region of the utility function.

From Proposition 2 and (3), only if utility value is in the convex region of the utility function, the mobile is allocated the data rate that is less than its maximum data rate. Therefore, at the optimal power and rate allocation, at most one mobile among the selected mobiles for transmission is allocated the data rate that is less than its maximum data rate, since at most one mobile among the selected mobiles for transmission achieves utility value in the convex region of the utility function.

APPENDIX IX
PROOF OF PROPOSITION 7

This is equivalent to the situation when there exist two mobiles, mobile n and mobile m, in the same cell. Mobile n has f_i, $R_i^{\max}$, $\lambda_i^{\max}(n,t)$, and $A_i(n,t)$. Mobile m has f_i, $R_i^{\max}$, $\lambda_i^{\max}(m,t)$, and $A_i(m,t)$. By Corollary 3, if $\lambda_i^{\max}(n,t) < \lambda_i^{\max}(m,t)$, then $A_i(n,t) \ge A_i(m,t)$. However, $A_i(n,t) \ne A_i(m,t)$, since if $A_i(n,t) = A_i(m,t)$, $\lambda_i^{\max}(n,t) = \lambda_i^{\max}(m,t)$, which is contradiction to the assumption. Therefore, $A_i(n,t) > A_i(m,t)$.

APPENDIX X
PROOF OF PROPOSITION 8

Since mobiles i and j are in the same condition, $P_i(\lambda) = P_j(\lambda)$. From (4), $P_i(\lambda)$ is nonincreasing as λ is increasing. Therefore, $P_i(\lambda^*(n,t)) \ge P_j(\lambda^*(m,t))$, since $\lambda_i^*(n,t) < \lambda_j^*(m,t)$.

REFERENCES

[1] S.-J. Oh and K. M. Wasserman, "Optimality of greedy power control and variable spreading gain in multi-class CDMA mobile networks," in *Proc. ACM Mobicom*, 1999, pp. 102–112.

[2] S.-J. Oh, T. L. Olsen, and K. M. Wasserman, "Distributed power control and spreading gain allocation in CDMA data networks," in *Proc. IEEE INFOCOM*, vol. 2, 2000, pp. 379–385.

[3] A. Bedekar, S. Borst, K. Ramanan, P. Whiting, and E. Yeh, "Downlink scheduling in CDMA data networks," in *Proc. IEEE GLOBECOM*, vol. 5, 1999, pp. 2653–2657.

[4] F. Berggren, S.-L. Kim, R. Jäntti, and J. Zander, "Joint power control and intracell scheduling of DS-CDMA nonreal time data," *IEEE J. Sel. Areas Commun.*, vol. 19, no. 10, pp. 1860–1870, Oct. 2001.

[5] S. V. Hanly, "An algorithm for combined cell-site selection and power control to maximize cellular spread spectrum capacity," *IEEE J. Sel. Areas Commun.*, vol. 13, no. 7, pp. 1332–1340, Sep. 1995.

[6] R. D. Yates and C.-Y. Huang, "Integrated power control and base-station assignment," *IEEE Trans. Veh. Technol.*, vol. 44, no. 3, pp. 638–644, Aug. 1995.

[7] C. U. Saraydar, N. B. Mandayam, and D. J. Goodman, "Power control in a multicell DMA data system using pricing," in *Proc. IEEE VTC'00-Fall*, vol. 2, 2000, pp. 484–491.

[8] CDMA 2000 High Rate Packet Data Air Interface Specification, Version 4, C.S0024-0 v 4.0, IS-856 TIA standard, 3GPP2. (2002, Oct.). [Online]. Available: http://www.3gpp2.org

[9] P. Bender, P. Black, M. Grob, R. Padovani, N. Sindhushayana, and A. Viterbi, "CDMA/HDR: a bandwidth-efficient high-speed wireless data service for nomadic users," *IEEE Commun. Mag.*, vol. 38, no. 7, pp. 70–77, Jul. 2000.

[10] Y. Jou, "Developments in third generation (3G) CDMA technology," in *Proc. IEEE ISSSTA'00*, 2000, pp. 460–464.

[11] S. Parkvall, E. Dahlman, P. Frenger, P. Beming, and M. Persson, "The evolution of WCDMA toward higher speed downlink packet data access," in *Proc. IEEE VTC'01-Spring*, vol. 3, 2001, pp. 2287–2291.

[12] M. Frodigh, S. Parkvall, C. Roobol, P. Johansson, and P. Larsson, "Future-generation wireless networks," *IEEE Pers. Commun.*, vol. 8, no. 5, pp. 10–17, Oct. 2001.

[13] R. D. Yates, "A framework for uplink power control in cellular radio systems," *IEEE J. Sel. Areas Commun.*, vol. 13, no. 7, pp. 1341–1347, Sep. 1995.

[14] S. Nanda, K. Balachandran, and S. Kumar, "Adaptation techniques in wireless packet data services," *IEEE Commun. Mag.*, vol. 38, no. 1, pp. 54–64, Jan. 2000.

[15] J.-W. Lee, R. R. Mazumdar, and N. B. Shroff, "Downlink power allocation for multi-class CDMA wireless networks," in *Proc. IEEE INFOCOM*, vol. 3, 2002, pp. 1480–1489.

[16] ——, "Downlink power allocation for multi-class wireless systems," *IEEE/ACM Trans. Netw.*, vol. 13, no. 4, pp. 854–867, Aug. 2005.

[17] R. Prasad and T. Ojanpera, "An overview of CDMA evolution toward wide-band CDMA," *IEEE Commun. Surveys Tutorials*, vol. 1, no. 1, pp. 2–29, 4th Quarter 1998. [Online]. Available: http://www.comsoc.org/pubs/surveys.

[18] M. Andrews, K. Kumaran, K. Ramanan, A. Stolyar, P. Whiting, and R. Vijayakumar, "Providing quality of service over a shared wireless link," *IEEE Commun. Mag.*, vol. 39, no. 2, pp. 150–154, Feb. 2001.

[19] J. G. Proakis, *Digital Communications*, 4th ed. New York: McGraw-Hill, 2000.

[20] G. Stuber, *Principles of Mobile Communication*. Norwell, MA: Kluwer Academic, 1996.

Jang-Won Lee (S'02–M'04) received the B.S. degree in electronic engineering from Yonsei University, Seoul, Korea, in 1994, the M.S. degree in electrical engineering from the Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Korea, in 1996, and the Ph.D. degree in electrical and computer engineering from Purdue University, West Lafayette, IN, in 2004.

During 1997–1998, he was with the Dacom R&D Center, Daejeon, Korea. During 2004–2005, he was a Postdoctoral Research Associate in the Department of Electrical Engineering, Princeton University, Princeton, NJ. Since September 2005, he has been an Assistant Professor in the School of Electrical and Electronic Engineering, Yonsei University, Seoul, Korea. His research interests include resource allocation, QoS and pricing issues, optimization, and performance analysis in communication networks.

Ravi R. Mazumdar (M'83–SM'94–F'05) was born in Bangalore, India. He received the B.Tech. degree in electrical engineering from the Indian Institute of Technology, Bombay, India, in 1977, the M.Sc. DIC in control systems from Imperial College, London, U.K., in 1978, and the Ph.D. degree in systems science from the University of California, Los Angeles, in 1983.

He is currently a Professor of electrical and computer engineering and holder of a University Research Chair at the University of Waterloo, Waterloo, Canada. From 1985 to 1988, he was an Assistant Professor in the Department of Electrical Engineering, Columbia University, New York, NY, where he was also a member of the Center for Telecommunications Research. From 1988 to 1996, he was a Professor at INRS-Telecommunications, Montreal, Canada, a graduate research institute affiliated with the University of Quebec, and held an invited appointment in the Department of Electrical Engineering, McGill University, Montreal. From 1996 to 1999, he was a Professor of mathematics at the University of Essex, Colchester, U.K. From 1999 to 2004, he was a Professor of electrical and computer engineering at Purdue University, West Lafayette, IN. He has held visiting positions and sabbatical leaves at UCLA, the University of Twente, The Netherlands, the Indian Institute of Science, Bangalore, and the Ecole Nationale Superieure des Telecommunications, Paris, France. His research interests are in wireless and wireline networks; applications of game theory to networking; applied probability, queueing theory, and stochastic analysis with applications to traffic engineering, statistical filtering theory, and mathematical finance.

Dr. Mazumdar is a Fellow of the IEEE and the Royal Statistical Society. He is a member of the working groups WG6.3 and 7.1 of the IFIP and a member of SIAM and the IMS.

Ness B. Shroff (S'91–M'93–SM'01) received the Ph.D. degree from Columbia University, New York, NY, in 1994. He has been with Purdue University, West Lafayette, IN, since 1994, where he is currently a Professor of electrical and computer engineering.

His research interests span the areas of wireless and wireline communication networks. He is especially interested in fundamental problems in the design, performance, control, security, and pricing of these networks. His research has been funded by various companies including Intel, Hewlett Packard, Nortel, AT&T, BAE systems, and L.G. Electronics, and government agencies including the National Science Foundation, DARPA, Indiana Department of Transportation, and the Indiana 21st Century Fund.

Dr. Shroff is an editor for the IEEE/ACM TRANSACTIONS ON NETWORKING and the *Computer Networks Journal*, and past editor of IEEE COMMUNICATIONS LETTERS. He was the Technical Program co-chair for IEEE INFOCOM'03 (San Francisco, CA), the panel co-chair for ACM Mobicom'02 (Atlanta, GA), program co-chair for the symposium on high-speed networks, IEEE Globecom 2001 (San Francisco, CA), and conference chair for the 14th Annual IEEE Computer Communications Workshop (Estes Park, CO). He was a the co-organizer of the NSF Workshop on Fundamental Research in Networking, April 2003. He received the NSF Career Award in 1996 and the *Computer Network Journal*'s Best Paper Award of 2003.