Optimal Resource Allocation for Data Service in CDMA Reverse Link

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Abstract— **The optimal resource allocation policy is studied for non-real-time users in CDMA reverse link. The resource allocation policy of interest includes channel coding, spreading gain control and power allocation under the conventional receiver operation. The constraints in the optimization include peak transmit power of the mobile station, total received power at the base station and QoS in the form of minimum SINR for each user. The coding and spreading gain control can be separated from the power allocation strategy. Our results show that the optimal power allocation policy depends on the objective function: a greedy policy is optimal to maximize the sum of throughput from each user, whereas a fair policy is optimal to maximize the product of throughput from each user. A unified approach is taken to derive the optimal policies, and it can also be applied to other power allocation problems in CDMA reverse link. Numerical results of the channel capacity are presented for both objectives along with the effect of QoS constraints.**

Index Terms— **Code division multiaccess, information rates, land mobile radio cellular systems, nonlinear programming, resource management.**

I. Introduction

Direct Sequence-Code Division Multiple Access (DS-CDMA) has been adopted as the core technology for multiple 3G cellular systems [1], including W-CDMA and CDMA2000. These 3G systems provide a wide variety of different communication services, such as real-time services including voice, video, and non-real-time or delay-tolerant data services including web-browsing, ftp, e-mail, etc. Since the multiple users interfere with each other in CDMA systems [2], it is crucial to allocate and control the power and rate of each user. For those using the non-real-time services, their delay tolerance can be exploited to enhance system performance.

In this paper, we consider the optimal resource allocation policy for the non-real-time users in DS-CDMA reverse link. It includes the allocation of the users' transmit power, the allocation of the users' rate through the spreading gain control and the selection of the channel coding for error detection or error correction. The objective is to optimize system performance on the basis that each user's Quality-of-Service (QoS) requirement is satisfied and the total interference to the real-time users in the same cell/sector.

The resource allocation in CDMA systems has captured considerable attention during the past years. Hanly and Tse provided a survey in [3] on the characterization of the capacity region, i.e., the capacity vector consisting of the achievable throughput for each user, and the corresponding power control. In our work, we are more interested in optimizing the performance of the entire cell/sector instead of that of each individual user. One important objective in optimizing system performance is to maximize the total sector/cell throughput or the spectral efficiency. In [4], the information theoretical bounds are maximized. In [5], the asymptotically optimal power allocation is obtained when the number of users approach infinity. A common feature in the previous work on this issue, including [4] and [5], is that the advanced multi-user detection [6] is assumed at the receiver. Since the advanced multi-user detection has not been implemented in any of the current and proposed 3G DS-CDMA systems due to its computational complexity, we do not assume it in our work. Similar to this work, the throughput maximization based on the common matched-filter receiver is studied in [7], but its formulation is restrictive since only the spreading gain control is considered.

Apart from maximizing the total throughput, in a more general form, optimal resource allocation should be designed to maximize the sum of utility functions from each user. Utility functions are formally defined in microeconomics [8] and can be intuitively understood as a quantitative description of the users' satisfaction. Maximization of the total throughput is one special case of this general formulation where the utility function is simply the throughput. Although there has been no consensus on the exact form of the user's utility as a function of its throughput, it is widely recognized that for a delay-tolerant data user, or an "elastic user" according to Shenker in [9], such a function should be increasing, concave and continuously differentiable. Kelly proposed using the logarithm as the utility function in [10], and it leads to the "proportional fair" rate allocation policy in the wired network. Since then, this function and the proportional fair design have been studied in various problems in the wired networks [11], [12]. In the context of wireless networks, the proportional fair principle has been adopted in the forward link scheduler design in the CDMA2000 1xEV-DO(1x EVolution Data Optimized) high speed packet data system [13]. A similar idea has been applied to the CDMA2000 reverse link in [14], but it requires the multiple users be Time-Division-Multiplexed(TDM) rather than Code-Division-Multiplexed(CDM). Thus significant signaling

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overhead must be added and backward compatibility can be lost. One of the results in this paper shows the proportional fair allocation for the reverse link on the CDM basis.

In this paper, we formulate the optimal resource allocation as utility maximization problems. The constraints in our optimization includes peak transmit power, total received power from all the data users and a minimum Signal-to-Interference-plus-Noise-Ratio (SINR) for each user for QoS or fairness commitment. In our work, a general methodology in searching and proving the optimal policy is discovered, which is applicable to a broad range of resource allocation designs. As examples, we show the optimal policies for two types of utility functions: one is linear with respect to the throughput, which makes the optimization the same as the maximization of the total throughput; the other is the logarithm of the throughput, which makes the optimization equivalent to the maximization of the product of users' throughput. The product maximization leads to a policy similar to the "proportional fair" allocation but the presence of the advanced multi-user interference complicates the policy and its derivation. For each of these two objectives, we consider two formulations: one is with fixed coding but the spreading gain and power are controlled; the other is with optimal codes in the sense that the Shannon capacity [16] for each single user is attained.

In CDMA systems, multiple users interfere with each other [2]. The concavity in the utility function only exists with respect to an individual user's power but not the power vector. This makes the non-linear optimization much more challenging [17]. However, our general method provides important structures which often result in simple search for the optimal policies. The assumption of peak power constraint separates our work from previous works like [18], where the constraints are on the average transmit power. Moreover, the absence of the advanced multi-user detection is another dividing line between our work and previous works.

The rest of the paper is organized as follows. The optimization problems with constraints are formulated in Section II. The methodology to solve the optimization problems is presented in Section III. In Section IV, the methodology presented in Section III is used to solve the problems defined in Section II. Numerical examples are presented in Section V. This paper concludes with final remarks and future work in Section VI.

II. Optimization Formulations

We consider a time-slotted system. Let M be the number of non-real-time data users in the CDMA cell/sector and their reverse link channel gains are ordered as $g_1 > g_2 > \cdots > g_M$. Without losing generality, we assume that no two users have the same channel gain. Vector $\mathbf{g} = (g_1, g_2, \cdots, g_M)$ includes channel gains of all the users. We also assume that $\mathbf{g}$ is known to the base station at the start of each time slot and all $g_i, i = 1, 2, \cdots, M$, remain constant during each time slot. Vector $\mathbf{p} = (p_1, p_2, \cdots, p_M)$ is the transmit power of all the users, allocated by the base station. We use vector $\mathbf{p}_{-i} = (p_1, p_2, \cdots, p_{i-1}, p_{i+1}, \cdots, p_M)$ for the power of all the other users except user i. Suppose that the matched filter receiver is used at the base station, namely there is no advanced multi-user detection. Then, the Signal-to-Interference-plus-Noise-Ratio (SINR) of user i, γ_i becomes

$$\gamma_i = \frac{p_i g_i}{I + \alpha \sum_{k \neq i} p_k g_k}, \quad \text{where} \quad i = 1, 2, \cdots, M. \quad (1)$$

In (1), parameter α is included for generality. According to [2], in practical systems, $\alpha \approx 1$.

As previously stated, we have two types of assumptions on the channel coding in this paper: one assumes an arbitrary but fixed coding at the symbol level; the other uses the Shannon coding, namely the 'optimal' codes achieving the information theoretical channel capacity for each individual user. In the first case(fixed coding), as shown in [7], the optimal spreading gain can be obtained separately from the power allocation. In the second case(Shannon coding), the codes can be determined by well-known result in information theory [16], again separately from the power allocation. Henceforth we focus on the power allocation part in this paper.

In the following, we list four example formulations: two of them with fixed coding and the other two with Shannon coding; at the same time, two of them with sum of throughput and the other two with product of throughput(sum of log-throughput). All of them are solved later in Section IV by our unified method presented in Section III.

A. Total Throughput Maximization With Fixed Coding

Suppose we have chosen a specific but fixed coding scheme on the symbol level. We have spreading gain and power at our control. This problem is formulated in [7]. As shown there, the optimal spreading gain can be determined independently from power allocation: at any power level, the optimal spreading gain is always inversely proportional to the chip-level SINR, where the proportion is dependent on the selected coding scheme. Consequently, maximizing the total throughput is equivalent to maximizing the sum of SINR. Therefore, essentially we have the following optimization problem:

$$(P1) \quad \max_{\mathbf{p} \in \mathcal{C}} J_1(p_1 g_1, p_2 g_2, \cdots, p_M g_M)$$

where

$$J_1 = \sum_{i=1}^{M} \frac{p_i g_i}{I + \alpha \sum_{k=1, k \neq i}^{M} p_k g_k}. \quad (2)$$

Note that the code-dependent scaling factor and the total bandwidth term are suppressed in (2).

The constraint, $\mathcal{C}$, considered throughout the paper consists of three individual constraints by $\mathcal{C} = \mathcal{C}_{p_{\max}} \cap \mathcal{C}_{QoS} \cap \mathcal{C}_{P_R^{\max}}$. Each constraint is defined as follow:

- $\mathcal{C}_{p_{\max}} = \{\mathbf{p} : 0 \leq p_i \leq p_{max}, \text{ for all } i = 1, 2, \cdots, M\}$, and it is the peak power constraint. This is due to the mobile stations' battery limitation and radiation regulation.
- $\mathcal{C}_{QoS} = \{\mathbf{p} : \gamma_i \geq \Lambda, \text{ for all } i = 1, 2, \cdots, M\}$, and it is the QoS constraint. This QoS constraint is motivated by the observation that the optimal power allocation, without such a constraint, may be greedy and unfair.
- $\mathcal{C}_{P_R^{\max}} = \left\{\mathbf{p} : \sum_{i=1}^{M} p_i g_i \leq P_R^{max}\right\}$, and it is the total received power constraint. It is due to the fact that the total received power from the data users is an interference

to other classes of users, like the voice users in the same sector/cell.

We assume that the QoS constraint can be met for all the users. In other words, we assume that the feasibility condition is satisfied, and in practice, this can be achieved by network planning and admission control [19].

$(P1)$ without QoS constraint is solved in [7] using elementary proof. Here we apply our general approach which greatly simplifies the derivation and extends their result.

B. Maximizing Total Capacity

In the above subsection, a specific coding is chosen and fixed. Suppose we relax this limitation and assume that the coding scheme on the symbol level is chosen to achieve the channel capacity for each single user without the multiuser detection. Based on the well known Shannon capacity result [16], we have the following optimization problem:

$$(P2) \quad \max_{\mathbf{p}\in\mathcal{C}} J_2(p_1 g_1, p_2 g_2, \cdots, p_M g_M)$$

where

$$J_2 = \sum_{i=1}^{M} \log\left(1 + \frac{p_i g_i}{I + \alpha \sum_{k=1,k\neq i}^{M} p_k g_k}\right). \qquad (3)$$

The constraints are the same as the one in the previous formulation. All through this paper, for the convenience of notation, the bandwidth term is suppressed from the capacity formula and natural logarithm is used instead of '$\log_2$'. Note that the effect of spreading gain control is absorbed by the capacity-achieving codes.

$(P2)$ with $\alpha = 1$ has been solved in [15] using elementary proof. Here we apply our general approach which greatly simplifies the derivation and extends their result.

C. Maximizing the Product of Throughput With Fixed Coding

Since maximizing the total summed throughput even with QoS constraint may lead to unfair policy, it is proposed to consider maximizing the product of each user's throughput. This can be seen as a "proportional fair" formulation. If we assume a fixed coding scheme, the result on the optimal spreading gain in [7] still applies. Thus maximizing the product of throughput is equivalent to maximizing the product of SINR. Therefore we have the following optimization problem:

$$(P3) \quad \max_{\mathbf{p}\in\mathcal{C}} J_3(p_1 g_1, p_2 g_2, \cdots, p_M g_M)$$

where

$$J_3 = \prod_{i=1}^{M} \frac{p_i g_i}{I + \alpha \sum_{k=1,k\neq i}^{M} p_k g_k}. \qquad (4)$$

As seen later, even without the QoS constraint, the QoS is guaranteed for each user by the optimal policy.

D. Maximizing the Product of Channel Capacity

We can have a similar formulation based on the optimal coding at symbol level for each individual user without the multiuser detection. Therefore the optimization problem is as follows:

$$(P4) \quad \max_{\mathbf{p}\in\mathcal{C}} J_4(p_1 g_1, p_2 g_2, \cdots, p_M g_M)$$

where

$$J_4 = \prod_{i=1}^{M} \log\left(1 + \frac{p_i g_i}{I + \alpha \sum_{k=1,k\neq i}^{M} p_k g_k}\right). \qquad (5)$$

III. Methodology in Optimization

A. General Properties of Optimal Solutions

Define $x_i = p_i g_i$ as the received power of user i, and $\mathbf{x} = (x_1, x_2, \cdots, x_M)$ as the vector of received powers. In the sequel, we interchangeably use the received power vector $\mathbf{x}$ and the transmit power vector $\mathbf{p}$. The solution of the optimization problem begins with an application of the Kuhn-Tucker condition [17]. Note that each $J_n(\mathbf{x})$ of the four formulations, is symmetric to any interchange of user indices. This is generally the case in the reverse link resource allocation problems without the advanced multi-user detection. Few properties of J are drawn using this symmetry.

The following is a re-write of the optimization problem[1] with the constraints in a linear form:

$$\max_{\mathbf{x}\in\mathcal{C}} J(\mathbf{x}), \qquad (6)$$

where $\mathcal{C} = \mathcal{C}_{p_{\max}} \cap \mathcal{C}_{QoS} \cap \mathcal{C}_{P_R^{\max}}$, and each constraint in a linear form is as follow:

$$\mathcal{C}_{p_{\max}} : \frac{x_i}{g_i} - p_{max} \leq 0, \forall i \in \{1, 2, \cdots, M\}. \qquad (7)$$

$$\mathcal{C}_{QoS} : -x_i + \alpha\Lambda \sum_{\substack{k=1\\k\neq i}}^{M} x_k + \Lambda I \leq 0, \forall i \in \{1, 2, \cdots, M\}. \qquad (8)$$

$$\mathcal{C}_{P_R^{\max}} : \sum_{j=1}^{M} x_j - P_R^{max} \leq 0. \qquad (9)$$

With $2M+1$ Lagrange multipliers ($\theta_1, \cdots, \theta_M, \lambda_1, \cdots, \lambda_M, \mu$), the complete Lagrange, denoted as $\mathcal{L}$, becomes as follow:

$$\begin{aligned}
\mathcal{L} &= J - \sum_{i=1}^{M} \theta_i \left(\frac{x_i}{g_i} - p_{max}\right) \\
&\quad - \sum_{i=1}^{M} \lambda_i \left(-x_i + \alpha\Lambda \sum_{k=1,k\neq i}^{M} x_k + \Lambda I\right) \\
&\quad - \mu \left(\sum_{j=1}^{M} x_j - P_R^{max}\right) \\
&= J - \sum_{i=1}^{M} \left(\theta_i + \mu - \lambda_i + \alpha\Lambda \sum_{k=1,k\neq i}^{M} \lambda_k\right) x_i \\
&\quad + \text{ some constant.}
\end{aligned} \qquad (10)$$

[1] In this section, as the derivation is common for all four of J_n's, the subscript is dropped.

From the Kuhn-Tucker condition, for optimum $\mathbf{x}$'s, we have $\frac{\partial \mathcal{L}}{\partial x_i} = 0, i = 1, 2, \cdots, M$, so

$$\frac{\partial J}{\partial x_i} = \frac{\theta_i}{g_i} + \mu - \lambda_i + \alpha\Lambda \sum_{k=1,k\neq i}^{M} \lambda_k. \quad (11)$$

Also we have the "non-negativity" and the "complimentary slackness"; all $2M+1$ Lagrange multipliers are non-negative and if a constraint is met with strict inequality (non-binding), then the corresponding Lagrange multiplier is zero.

Note that $\mathcal{C}_{P_R^{\max}}$ is on all the users, so the value of μ is common to all the users. We can classify all M users into the following three disjoint groups according to the binding constraints - depending upon λ_i and/or θ_i are zero:

- Users with QoS-binding: Denote this group as A_1. Then for user j, $j \notin A_1$, $\lambda_j = 0$, and for user i, $i \in A_1$

$$\frac{\partial J}{\partial x_i} = \frac{\theta_i}{g_i} + \mu - \lambda_i + \alpha\Lambda \sum_{k\neq i, k\in A_1} \lambda_k. \quad (12)$$

  We include θ_i in (12) in order to incorporate the possibility that a user may transmit at $p_{\max}$ to meet the QoS requirement, and $\theta_i = 0$ is if and only if user i transmits with strictly less than $p_{\max}$.
- Users with neither QoS nor peak-power binding: Denote this group as A_2. Then, for user i, $i \in A_2$

$$\frac{\partial J}{\partial x_i} = \mu + \alpha\Lambda \sum_{k\in A_1} \lambda_k. \quad (13)$$

- Users with peak-power-binding but no QoS-binding: Denote this group as A_3. Then, for user i, $i \in A_3$

$$\frac{\partial J}{\partial x_i} = \frac{\theta_i}{g_i} + \mu + \alpha\Lambda \sum_{k\in A_1} \lambda_k. \quad (14)$$

In the following subsections, we derive the structure of the optimal solution conditioning that the polarities of $\left(\frac{\partial J}{\partial x_i} - \frac{\partial J}{\partial x_j}\right)$ and $(x_i - x_j)$ are either always the same or always the opposite. Define sign$(\cdot)$ as follow.

$$\text{sign}(x) = \begin{cases} \frac{x}{|x|}, & \text{for } x \neq 0, \\ 0, & \text{for } x = 0. \end{cases} \quad (15)$$

B. Same-Sign Condition, i.e. sign $\left(\frac{\partial J}{\partial x_i} - \frac{\partial J}{\partial x_j}\right) =$ *sign* $(x_i - x_j)$

One word on notation: in the following derivation, the term "QoS-achieving power" means the minimum power p_i such that user i satisfies the QoS constraint when $\mathbf{p}_{-i}$ is fixed. This power level is not a constant, but dependent on $\mathbf{p}_{-i}$. Also "intermediate power" means strictly higher than the "QoS-achieving power" but strictly less than the maximum power, $p_{\max}$.

Lemma 1 *For an optimum solution, there can be at most one user with intermediate power. In other words, number of users in group* A_2 *is at most one.*

Proof: Suppose that $\mathbf{x}^*$ is a optimum solution of (6), with $x_i^* = p_i^* g_i$ and $x_j^* = p_j^* g_j$, where p_i^* and p_j^* are strictly between their respective QoS-achieving powers and p_{max}. As user i and j are both in group A_2, from (13) we have $\frac{\partial J}{\partial x_i} = \frac{\partial J}{\partial x_j}$. Therefore, from the same-sign condition $x_i^* = x_j^*$. We can find $\delta > 0$, such that

$$\mathbf{x}_\delta^* = (x_1, \cdots, x_i + \delta, \cdots, x_j - \delta, \cdots, x_M), \text{ with } \mathbf{x}_\delta^* \in \mathcal{C}.$$

Then,

$$J(\mathbf{x}_\delta^*) - J(\mathbf{x}^*) = \int_0^\delta \frac{\partial J}{\partial \tilde{\delta}}\, d\tilde{\delta}, \quad (16)$$

where

$$\frac{\partial J}{\partial \tilde{\delta}} = \left(\frac{\partial J}{\partial x_i} - \frac{\partial J}{\partial x_j}\right)\Bigg|_{\mathbf{x}=\mathbf{x}_{\tilde{\delta}}^*} > 0, \quad \text{for any } 0 < \tilde{\delta} < \delta. \quad (17)$$

Therefore, we can find $\mathbf{x}_\delta^* \in \mathcal{C}$, such that $J(\mathbf{x}_\delta^*) > J(\mathbf{x}^*)$. This is a contradiction. □

In the following, we present an approach to find the optimal solution of (6) under the same-sign condition by reducing the solution space. Reduction of the solution space can be done by ignoring some forms of $\mathbf{x}$ without losing optimality. A specific form of $\mathbf{x}$ is ignored as a potential optimal solution, if an optimal solution cannot exist with that specific form, or we can find $\mathbf{y}$ in another form of consideration such that $J(\mathbf{y}) = J(\mathbf{x})$. Lemma 2 characterizes the solution space when there is no intermediate user. When there exists one and only one intermediate user, Lemma 3 and 4 delineates the distribution of users in group A_1 and A_3.

Lemma 2 *Considering the case when there is no intermediate user, we can restrict our attention of an optimal solution to the following cases without losing optimality; any user with* p_{max} *has a higher channel gain than the users with QoS-achieving.*

Proof: Suppose that $\mathbf{x}^*$ is an optimum solution of (6), with $x_k^* = p_{\max} g_k$ or $\gamma_k^* = \Lambda$, for all $k \in \{1, 2, \cdots, M\}$, i.e. no intermediate user. Suppose that $g_i > g_j$, $p_i^* < p_{\max}$ and $\gamma_j^* > \Lambda$, i.e. user i and j belong to group A_1 and A_3, respectively. From (13) and (14), $\frac{\partial J}{\partial x_i} < \frac{\partial J}{\partial x_j}$, and from the same-sign condition, $x_i^* < x_j^*$. Define $\mathbf{x}^{**}$ such that $x_k^{**} = x_k^*$ for $k \in \{1, 2, \cdots, M\}$, except $x_i^{**} = x_j^*$ and $x_j^{**} = x_i^*$. As $x_i^* < x_j^*$, $\mathbf{x}^{**} \in \mathcal{C}$. Note that $J(\mathbf{x}^*) = J(\mathbf{x}^{**})$ while $\mathbf{x}^{**} \in \mathcal{C}$, and $\mathbf{x}^{**}$ has one intermediate user of user j. Therefore, if $\mathbf{x}^*$ is the optimal solution without an intermediate user, then we can find $\mathbf{x}^{**}$ which is also an optimal solution with one intermediate user. □

Lemma 3 *If an optimal solution has one and only one intermediate user, the users with lower channel gains than the intermediate user's, meet the QoS-constraint with equality.*

Proof: Suppose that $\mathbf{x}^*$ is an optimum solution of (6) and there exists i and j such that $g_i > g_j$, $p_i^* < p_{\max}$, $\gamma_i^* > \Lambda$ and $\gamma_j^* > \Lambda$. Following the same way as in the proof of Lemma 2, by exchanging the received power of user i and j, we can find $\mathbf{x}^{**} \in \mathcal{C}$ such that $J(\mathbf{x}^*) = J(\mathbf{x}^{**})$. Then, $\mathbf{x}^{**}$ has two intermediate users – user i and j. From Lemma 1, we can find $\mathbf{x}^{***} \in \mathcal{C}$ such that $J(\mathbf{x}^{***}) > J(\mathbf{x}^{**}) = J(\mathbf{x}^*)$. This is a contradiction. □

Lemma 4 *If an optimal solution has one and only one intermediate user, without losing optimality, we can restrict* *our attention of the optimal solution such that all users with higher channel gains than the intermediate user's, transmit with* $p_{\max}$.

Proof: Suppose that $\mathbf{x}^*$ is an optimum solution of (6) and there exists i and j such that $g_i > g_j$, $p_i^* < p_{\max}$, $\gamma_i^* = \Lambda$ and $p_j^* < p_{\max}$, $\gamma_j^* > \Lambda$, i.e. user i is a QoS-binding user and user j is an intermediate user. Then, by swapping x_i and x_j, we can achieve the same objective under the same constraint. By doing so, without losing optimality, we can ignore optimal solutions such that the intermediate user (the user in group A_2), if there is, has lower channel gain than the users with QoS-binding (the users in group A_3). □

From Lemma 1 to 4, an optimal solution can be found as follows. Slice the users into two classes - good and bad, based on their channel gains. For each of the $M+1$ possible ways of partitioning users, allocate the transmit power in the following fashion. Allocate p_{max} to all good users while the same received power u is received to all bad users just to meet the QoS requirement. There can be one exception - the user with the best channel gain among the bad users is allocated v $(> u)$, and this user is the possible intermediate user. Optimize the objective with respect to the two variables u and v, subject to constraints. Evaluate the objective, and compare the objective values for each possible slicing rule, u, and v. Pick the slice, u and v that yields the best value.

In summary, sign $\left(\frac{\partial J}{\partial x_i} - \frac{\partial J}{\partial x_j}\right) = \text{sign}\,(x_i - x_j)$ implies a greedy policy, namely the good users transmit p_{max}, and bad users transmit its QoS-achieving power while there can be at most one user in-between. Application of this optimal policy is shown in Proposition 1 of Section IV-A.

C. Opposite-Sign Condition, i.e. sign $\left(\frac{\partial J}{\partial x_i} - \frac{\partial J}{\partial x_j}\right) = -$*sign*$(x_i - x_j)$

Like in Section III-B, the derivation starts with paying attention to the intermediate users; users belong to group A_2.

Lemma 5 *For an optimum solution, if there are users with intermediate powers, their received powers should be the same.*

Proof: Suppose that $\mathbf{x}^*$ is a optimum solution of (6) with $\gamma_i^* > \Lambda$, $p_i^* < p_{\max}$, and $\gamma_j^* > \Lambda$, $p_j^* < p_{\max}$, i.e. user i and j are users with intermediate transmit power. Then both user i and j belong to group A_2. From (13), $\frac{\partial J}{\partial x_i} = \frac{\partial J}{\partial x_j}$, and therefore from sign $\left(\frac{\partial J}{\partial x_i} = \frac{\partial J}{\partial x_j}\right) = -\text{sign}(x_i - x_j)$, $x_i^* = x_j^*$. □

The following Lemmas delineate the distributions of users in group A_1 and A_3, with respect to the users in A_2.

Lemma 6 *Except the case where all the received powers are the same, if there exists a QoS-binding user, then the QoS-binding user transmit with* $p_{\max}$.

Proof: Suppose that $\mathbf{x}^*$ is an optimum solution of (6) with $\gamma_i^* = \Lambda$, $p_i^* < p_{\max}$, and $\gamma_j^* > \Lambda$, where $i, j \in \{1, 2, \cdots, M\}$ – in other words, user i belongs to A_1 and user j belongs to A_2 or A_3. From (10) and (11), as $\theta_i = 0$ due to $p_i^* < p_{\max}$, $\frac{\partial J}{\partial x_i} < \frac{\partial J}{\partial x_j}$. From the opposite-sign condition, this implies $x_i^* > x_j^*$. However, from the monotonicity of SINR equation shown in (1), $\gamma_i^* = \Lambda < \gamma_j^*$ implies that $x_i^* < x_j^*$. This is a contradiction. □

Lemma 7 *Except the case where all the received powers are the same, there can be at most one QoS-binding user and that user is with the worst channel gain.*

Proof: It can be readily shown from using Lemma 6 by the assumption that all the channel gains are different. □

Lemma 8 *For an optimum solution, if there exists user* i *such that* $p_i^* = p_{\max}$ *and* $\gamma_i^* > \Lambda$, *then* x_i^* *should be less than the received power from an intermediate user.*

Proof: If $\mathbf{x}^*$ is an optimum solution of (6), with $x_i^* = p_{\max}$ $\gamma_i^* > \Lambda$ and $x_j^* < p_{\max}$ $\gamma_j^* > \Lambda$, i.e. user i belongs to group A_3 and j belongs to group A_2, respectively. From (13) and (14), $\frac{\partial J}{\partial x_i} > \frac{\partial J}{\partial x_j}$, and from the opposite-sign condition $x_i^* < x_j^*$. □

Arriving at the optimal solution consists of the following steps: Slice the users into two classes, good and bad, based on channel gains. For each of the $M+1$ possible ways of partitioning users, allocate received power in the following fashion. Allocate the maximum transmit power to all bad users. Allocate equal received power u, to all remaining users while u is higher than any of the received power from the bad users. Optimize the value u subject to constraints. If a feasible solution is found, evaluate the resulting value of the objective function. Pick the slice that provides the best objective function with the corresponding u.

In summary, sign $\left(\frac{\partial J}{\partial x_i} - \frac{\partial J}{\partial x_j}\right) = -\text{sign}\,(x_i - x_j)$ implies a fair policy, namely the bad users transmit p_{max}; good users transmit with a same received power but higher than the one from any bad user. Application of this optimal policy is shown in Proposition 2 of Section IV-B.

IV. Solutions to Formulated Optimization Problems

In Section III, the general method is based on getting the relationship between sign $\left(\frac{\partial J}{\partial x_i} - \frac{\partial J}{\partial x_j}\right)$ and sign $(x_i - x_j)$. In this section, we solve the optimization problems based on this relationship. For the convenience of notation, we define $I_0 = I + \alpha \sum_{k=1,k\neq i,j}^{M} x_k$.

A. Summation Form of Optimization - $(P1)$ and $(P2)$

For $(P1)$ from Section II-A, we have

$$\frac{\partial J_1}{\partial x_i} = \frac{1}{I + \alpha \sum_{k=1,k\neq i}^{M} x_k} - \sum_{m=1,m\neq i}^{M} \frac{\alpha x_k}{(I + \alpha \sum_{k=1,k\neq m}^{M} x_k)^2} \qquad (18)$$

After canceling the common terms,

$$\frac{\partial J_1}{\partial x_i} - \frac{\partial J_1}{\partial x_j} = \left(I + \alpha \sum_{k=1}^{M} x_k \right) \times \left\{ \frac{1}{(I + \alpha \sum_{k=1,k\neq i}^{M} x_k)^2} - \frac{1}{(I + \alpha \sum_{k=1,k\neq j}^{M} x_k)^2} \right\}. \tag{19}$$

Then we have

$$\begin{aligned} \operatorname{sign}\left(\frac{\partial J_1}{\partial x_i} - \frac{\partial J_1}{\partial x_j} \right) &= \operatorname{sign}\left\{ \frac{1}{(I_0 + \alpha x_j)^2} - \frac{1}{(I_0 + \alpha x_i)^2} \right\} \\ &= \operatorname{sign}(x_i - x_j). \end{aligned} \tag{20}$$

Therefore, the optimal policy is greedy.

Also, for $(P2)$ from Section II-B, we have

$$\frac{\partial J_2}{\partial x_i} = \frac{1}{I + x_i + \alpha \sum_{k=1,k\neq i}^{M} x_k} - \sum_{\substack{m=1\\m\neq i}}^{M} \frac{\alpha x_m}{(I + \alpha \sum_{\substack{k=1\\k\neq m}}^{M} x_k)(I + x_m + \alpha \sum_{\substack{k=1\\k\neq m}}^{M} x_k)}. \tag{21}$$

After some manipulation, we have

$$\begin{aligned} &\operatorname{sign}\left(\frac{\partial J_2}{\partial x_i} - \frac{\partial J_2}{\partial x_j} \right) \\ &= \operatorname{sign}\left\{ \begin{array}{l} (I_0 + \alpha x_i)(I_0 + x_j + \alpha x_i) \\ -(I_0 + \alpha x_j)(I_0 + x_i + \alpha x_j) \end{array} \right\} \\ &= \operatorname{sign}\left\{ (x_i - x_j)\left(\alpha^2 (x_i + x_j) + (2\alpha - 1) I_0 \right) \right\}. \end{aligned} \tag{22}$$

If $\alpha \geq \frac{1}{2}$, we have $\operatorname{sign}\left(\frac{\partial J_2}{\partial x_i} - \frac{\partial J_2}{\partial x_j} \right) = \operatorname{sign}(x_i - x_j)$ and therefore a greedy policy is optimal. Since $\alpha \approx 1$ in practical systems [2], we have not lost too much generality.

Proposition 1 (Optimality of the greedy policy) *For $(P1)$ and $(P2)$, (if $\alpha \geq \frac{1}{2}$ for $(P2)$), without losing optimality, we can restrict our attention of an optimal power allocation vector to the following form:*

$$\mathbf{p}^* = (p_{\max}, \cdots, p_{\max}, p_{i_T}^*, p_{i_T+1}^*, p_{i_T+2}^*, \cdots, p_M^*) \tag{23}$$

where i_T is an integer, $1 \leq i_T \leq M$, $0 < p_{i_T}^* \leq p_{\max}$ and

$$\frac{p_m^* g_m}{I + \sum_{j=1}^{i_T - 1} p_{\max} g_j + \sum_{j=i_T, j\neq m}^{M} p_j^* g_j} = \Lambda, \ \forall m > i_T. \tag{24}$$

Proof: It can be readily shown from the same-sign property of J_1 and J_2.

B. Product Form of Optimization - $(P3)$ and $(P4)$

For $(P3)$ from Section II-C, we have

$$\begin{aligned} \frac{\partial J_3}{\partial x_i} &= \frac{1}{I + \alpha \sum_{k=1,k\neq i}^{M} x_k} \prod_{\substack{n=1\\n\neq i}}^{M} \frac{x_n}{I + \alpha \sum_{k=1,k\neq n}^{M} x_k} \\ &\quad - \sum_{\substack{m=1\\m\neq i}}^{M} \frac{\alpha x_m}{(I + \alpha \sum_{k=1,k\neq m}^{M} x_k)^2} \prod_{\substack{n=1\\n\neq m}}^{M} \frac{x_n}{I + \alpha \sum_{k=1,k\neq n}^{M} x_k} \\ &= J_3 \times \left\{ \frac{1}{x_i} - \sum_{\substack{m=1\\m\neq i}}^{M} \frac{\alpha}{(I + \alpha \sum_{k=1,k\neq m}^{M} x_k)} \right\}. \end{aligned} \tag{25}$$

After deleting the common terms, we have the following simple relationship:

$$\begin{aligned} \operatorname{sign}\left(\frac{\partial J_3}{\partial x_i} - \frac{\partial J_3}{\partial x_j} \right) &= \operatorname{sign}\left\{ \frac{1}{x_i (I_0 + \alpha x_i)} - \frac{1}{x_j (I_0 + \alpha x_j)} \right\} \\ &= -\operatorname{sign}(x_i - x_j) \end{aligned} \tag{26}$$

It implies that a fair policy is optimal.

Also, for $(P4)$ from Section II-D, we establish the relationship between $\operatorname{sign}\left(\frac{\partial J_4}{\partial x_i} - \frac{\partial J_4}{\partial x_j} \right)$ and $\operatorname{sign}(x_i - x_j)$ as follow. For convenience, define $L_i = \log\left(1 + \frac{x_i}{I + \alpha \sum_{k=1,k\neq i}^{M} x_k} \right)$. The partial derivative is shown in (27). After canceling common terms, we have

$$\frac{\partial J_4}{\partial x_i} - \frac{\partial J_4}{\partial x_j} = J_4 \times \left\{ \begin{array}{l} \dfrac{(I_0 + \alpha x_i + \alpha x_j)}{L_i (I_0 + \alpha x_j)(I_0 + x_i + \alpha x_j)} \\ - \dfrac{(I_0 + \alpha x_i + \alpha x_j)}{L_j (I_0 + \alpha x_i)(I_0 + x_j + \alpha x_i)} \end{array} \right\}. \tag{28}$$

Define

$$\Delta = L_i (I_0 + \alpha x_j)(I_0 + x_i + \alpha x_j) - L_j (I_0 + \alpha x_i)(I_0 + x_j + \alpha x_i), \tag{29}$$

then we have

$$\operatorname{sign}\left(\frac{\partial J_4}{\partial x_i} - \frac{\partial J_4}{\partial x_j} \right) = -\operatorname{sign}(\Delta). \tag{30}$$

Next, we connect $\operatorname{sign}(\Delta)$ with $\operatorname{sign}(x_i - x_j)$. Let x_j be fixed and the domain of x_i is $[0, \infty)$. At $x_i = 0$, $\Delta < 0$, and as $x_i \to \infty$, $\Delta \to \infty$. So a root for the equation $\Delta(x_i) = 0$, must exist. In the following, it is shown that $x_i = x_j$ is the unique root. As a reference, we have

$$\frac{\partial L_i}{\partial x_i} = \frac{1}{I_0 + x_i + \alpha x_j}, \text{ and} \tag{31}$$

$$\frac{\partial L_j}{\partial x_i} = -\frac{\alpha x_j}{(I_0 + \alpha x_i)(I_0 + x_j + \alpha x_i)}. \tag{32}$$

Then,

$$\begin{aligned} \frac{\partial \Delta}{\partial x_i} &= (I_0 + 2\alpha x_j) + \log\left(1 + \frac{x_i}{I_0 + \alpha x_j} \right)(I_0 + \alpha x_j) \\ &\quad - \alpha \log\left(1 + \frac{x_j}{I_0 + \alpha x_i} \right)(2I_0 + 2\alpha x_i + x_j). \end{aligned} \tag{33}$$

$$\frac{\partial J_4}{\partial x_i} = J_4 \times \left\{ \frac{1}{(I + x_i + \alpha \sum_{k=1,k\neq i}^{M} x_k) L_i} - \sum_{n=1,n\neq i}^{M} \frac{\alpha x_n}{(I + \alpha \sum_{k=1,k\neq n}^{M} x_k)(I + x_n + \alpha \sum_{k=1,k\neq n}^{M} x_k) L_n} \right\}. \quad (27)$$

At $x_i = 0$, the sign of (33) is not clear; but as $x_i \to \infty$, $\frac{\partial \Delta}{\partial x_i} \to \infty$. However, this is not enough to determine the sign of Δ or $\frac{\partial \Delta}{\partial x_i}$ with respect to the sign of $(x_i - x_j)$. So taking derivative again:

$$\frac{\partial^2 \Delta}{\partial {x_i}^2} = \frac{I_0 + \alpha x_j}{I_0 + x_i + \alpha x_j} + \frac{\alpha^2 x_j (2I_0 + 2\alpha x_i + x_j)}{(I_0 + \alpha x_i)(I_0 + \alpha x_i + x_j)} - 2\alpha^2 \log\left(1 + \frac{x_j}{I_0 + \alpha x_i}\right). \quad (34)$$

Again, at $x_i = 0$, the sign of (34) is not clear; but when $x_i \to \infty$, we have $\frac{\partial^2 \Delta}{\partial {x_i}^2} \sim \frac{1}{x_i} > 0$. In order to determine the sign of $\frac{\partial^2 \Delta}{\partial {x_i}^2}$, the third derivative can be investigated. After some algebraic manipulation, we have

$$\frac{\partial^3 \Delta}{\partial {x_i}^3} = -\frac{I_0 + \alpha x_j}{(I_0 + x_j + \alpha x_j)^2} - \frac{\alpha^3 x_j^3}{(I_0 + \alpha x_i)^2 (I_0 + \alpha x_i + x_j)^2} < 0. \quad (35)$$

Now we finally can conclude that $\frac{\partial^2 \Delta}{\partial {x_i}^2}$ is a decreasing function of x_i. As $\frac{\partial^2 \Delta}{\partial {x_i}^2}$ is positive at $x_i \to \infty$, it is positive for all $x_i > 0$. The fact that $\frac{\partial^2 \Delta}{\partial {x_i}^2} > 0$, implies that $\frac{\partial \Delta}{\partial x_i}$ is a monotonically increasing function of x_i. There are two cases to consider

- Case 1 : $\frac{\partial \Delta}{\partial x_i} > 0$ for all $x_i > 0$;
- Case 2 : $\frac{\partial \Delta}{\partial x_i} < 0$ for small x_i but $\frac{\partial \Delta}{\partial x_i} > 0$ for large x_i.

Since $\Delta < 0$ at $x_i = 0$ but $\Delta > 0$ when x_i large, in either case, the root of $\Delta(x_i) = 0$ is unique. The unique root is $x_i = x_j$, and the uniqueness of the root implies sign(Δ) = sign$(x_i - x_j)$. Overall, from (30) we have the conclusion that

$$\text{sign}\left(\frac{\partial J_4}{\partial x_i} - \frac{\partial J_4}{\partial x_j}\right) = -\text{sign}(x_i - x_j). \quad (36)$$

So $(P4)$ falls into the category that a fair policy is optimum.

Proposition 2 (Optimality of the fair policy) *For $(P3)$ and $(P4)$, without losing optimality, we can restrict our attention of the optimal power allocation vector to the following form:*

$$\mathbf{p}^* = (p_1^*, p_2^*, \cdots, p_{i_G}^*, p_{\max}, p_{\max}, \cdots, p_{\max}) \quad (37)$$

where i_G is an integer, $1 \le i_G \le M$, and $p_1^* g_1 = p_2^* g_2 = \cdots = p_{i_G}^* g_{i_G} \ge p_{\max} g_{i_G+1}$.

Proof: It can be readily shown from the opposite-sign property of J_3 and J_4. □

V. Numerical Examples

In this section, numerical examples for the total capacity under both sum throughput maximization and product throughput maximization are present. The impact of the QoS requirements is also discussed. Table I summarizes the configurations used in the numerical examples. Channel models and their related parameters are from [20]. Users are randomly (uniformly distributed) dropped over a single hexagonal cell, where the base station is located at the center of the cell. A set of dropped users is considered for the capacity computation only if there exists a power allocation solution that guarantees the minimum QoS requirements are satisfied. Otherwise, the entire users are re-dropped. In practice, the feasibility condition is assured by network planning and admission control [19]. Each user is assigned with a stationary channel gain, g_i, taking into account distance loss and log-normal shadowing. Since the optimization problem does not take into account the time-varying radio condition, fast fading and power control aspects are not considered in this study. The Rise-Over-Thermal (ROT) is a limitation on the total received power at the base station, and is defined in Table I.

TABLE I
CONFIGURATIONS FOR NUMERICAL RESULTS

Cell Structure	Single Hexagonal Cell
Cell Radius	1.0 km
Antenna Radiation	Omni-directional
Distance Loss (Propagation) Model	$28.6 + 35\log_{10}(d)$ dB, d in meters
Log-Normal Shadowing Standard Deviation	8.9 dB
Maximum transmit power from mobile station ($p_{\max}$)	0.2 Watt
Implementation loss after compensation from antenna gain	0 dB
Thermal noise variance (σ_{th}^2) at the base station	1.547×10^{-14} Watt ($= -138.1$dB)
Rise-Over-Thermal (ROT) $(P_B^{\max} + \sigma_{th}^2)/\sigma_{th}^2$	Maximum by 7 dB

Fig. 1 represents the capacity obtained when the transmit powers of the users are allocated to maximize the sum-capacity. All through this section, all the capacity numbers are normalized by the total bandwidth so that their unit is 'Bits/Sec/Hz'. In the "No-QoS requirement" case ($\Lambda = 0$), the multi-user diversity gain (opportunistic scheduling gain) is observed with a diminishing return. On the other hand, if there is a QoS requirement, the multi-user penalties (capacity decrease by increasing the number of users) are observed. As the number of the users increase, the statistics of the poor users gets worse, and more importantly the statistics of the poor channel quality users can drag the system capacity. Basically, as the maximum sum-capacity power allocation (summation form) is a greedy policy, the QoS requirements (fairness constraint) impacts a lot on the capacity of the system. Note that QoS requirements (-21 dB and -18 dB) are chosen to represent the typical SINR level for 9.6 Kbps traffic channel throughput maintenance and the reverse pilot channel maintenance, respectively [21].

Fig. 2 represents the capacity obtained when the powers are allocated to maximize the product of the user capacities. In this policy, even without a QoS-constraint, the power allocation strategy leads to a fair policy, and therefore the multi-user penalties are observed. Imposing QoS constraints

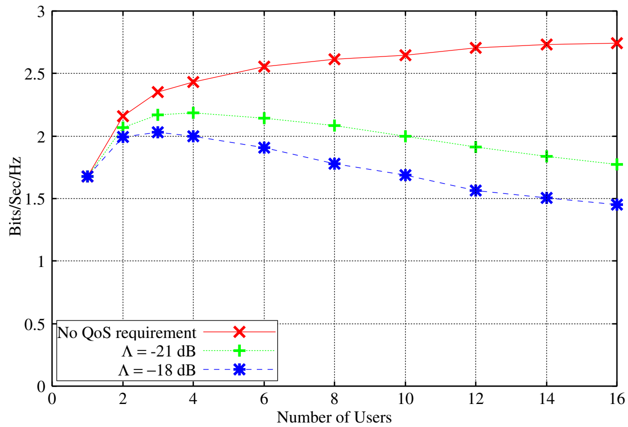

Fig. 1. Capacity of the system when the powers are allocated to maximize the sum-capacity of the system with different QoS requirements.

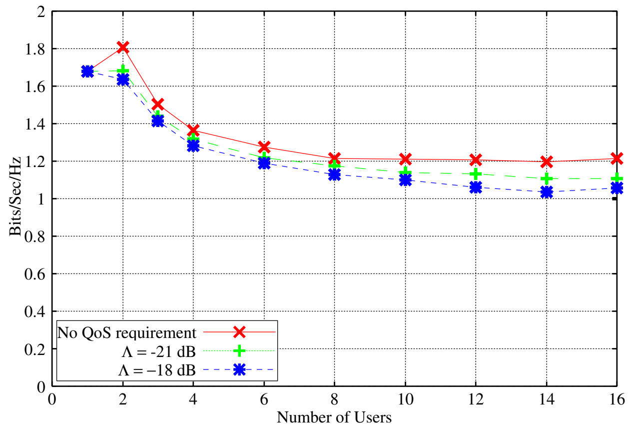

Fig. 2. Capacity of the system when the powers are allocated to maximize the product of user capacity with different QoS requirements.

to users decrease the throughput, but as the policy is inherently fair (QoS-aware), the impact is smaller than the case of the summation-form optimization.

Fig. 3 compares the CDF of user throughput under the two power allocation policies – addition and product form. To make a fair comparison, we choose the number of users $M = 8$ and the minimum SINR $\Lambda = -21$dB. In the overall average system throughput perspective, the addition-form optimization gives better performance. However, in the addition-form case, many users experience the minimum capacity, but the best channel quality user experience a very high capacity. In the product form case, the CDF represents more fair allocation of the radio resource, and the overall system capacity suffers from the statistics of poor channel quality users.

VI. Conclusions and Future Work

We have studied optimal resource allocation at the base station for non-real-time data users in the CDMA reverse link. We have focused on the power allocation since the channel coding and spreading gain control can be chosen separately. We have found a general approach in searching for the optimal policy. As examples, we have shown the throughput maximization and log-throughput maximization with peak transmit

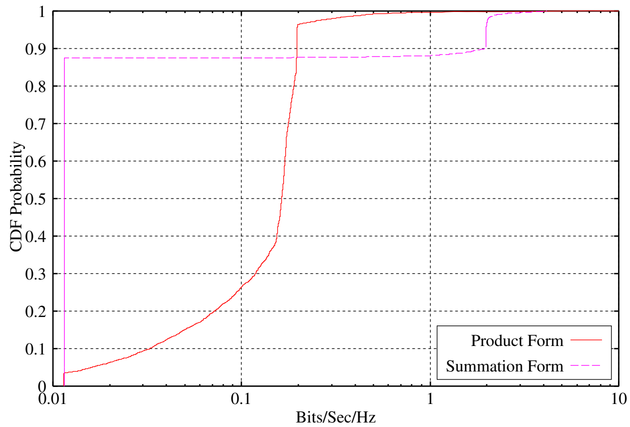

Fig. 3. CDF of user's throughput when 8 users are in the system with minimum SINR requirements of -21 dB.

power, total received power and QoS constraints. Throughput maximization results in a greedy power allocation whereas the log-throughput maximization results in a 'proportional fair' allocation. We have also studied the impact of different level of QoS constraint on the sector/cell performance.

Our future work includes the investigation of possible autonomous transmission scheme to achieve the optimal allocations. We also need to study multi-cell coordination and the extension to optimizations considering channel variation.

References

[1] Vijay K. Garg, *Wireless Network Evolution: 2G to 3G*. Upper Saddle River, NJ: Prentice Hall, 2002.

[2] A. J. Viterbi, *CDMA: Principles of Spread Spectrum Communication*. Boston, MA: Addison-Wesley, 1995.

[3] S. V. Hanly and D. N. Tse, "Power control and capacity of spread spectrum wireless networks," *Automatica*, vol. 35, no. 12, pp. 1987-2012, Dec. 1999.

[4] R. Knopp and P. A. Humblet, "Information capacity and power control in single-cell multiuser communications," in *Proc. IEEE ICC*, June 1995, pp. 331-335.

[5] P. Viswanath, D. N. Tse, and V. Anantharam, "Asymptotically optimal water-filling in vector multiple-access channels," *IEEE Trans. Inform. Theory*, vol. 47, no. 1, pp. 241-267, Jan. 2001.

[6] M. Honig, U. Madhow, and S. Verdu, "Blind adaptive multiuser detection," *IEEE Trans. Inform. Theory*, vol. 41, no. 4, pp. 955-960, July 1995.

[7] S.-J. Oh, D. Zhang, and K. M. Wasserman, "Optimal resource allocation in multi-service CDMA networks," *IEEE Trans. Wireless Commun.*, vol. 2, no. 4, pp. 811-821, July 2003.

[8] A. Mas-Colell, M. Whinston, and J. Green, *Microeconomic Theory*. Oxford, UK: Oxford University Press, 1995.

[9] S. Shenker, "Fundamental design issues for the future Intenet," *J. Select. Areas Commun.*, vol. 13, pp. 1176-1188, Sep. 1995.

[10] F. Kelly, A. Maulloo, and D. Tan, "Rate control in communication networks: Shadow prices, proportional fairness and stability," *J. Operational Research Society*, vol. 49, pp. 237-252, 1998.

[11] J. Mo and J. Walrand, "Fair end-to-end window-based congestion control," *IEEE/ACM Trans. Networking*, vol. 8, no. 5, pp. 556-567, Oct. 2000.

[12] S. H. Low, L. Peterson, and L. Wang, "Understanding TCP vegas: A duality model," *Perf. Evaluation Review*, vol. 29, no. 1, pp. 226-235, June 2001.

[13] A. Jalali, R. Padovani, and R. Pankaj, "Data throughput of CDMA-HDR a high efficiency-high data rate personal communication wireless system," in *Proc. IEEE 51st Veh. Technol. Conf.-Spring*, May 2000, pp. 1854-1858.

[14] J. Damnjanovic, A. Jain, T. Chen, and S. Sarkar, "Scheduling the cdma2000 reverse link," in *Proc. Veh. Technol. Conf.-Fall*, Sep. 2002, pp, 386-390.

[15] S.-J. Oh and A. C. K. Soong, "QoS-constrained information-theoretic sum capacity of reverse link CDMA systems," *IEEE Trans. Wireless Commun.*, vol. 5, no. 1, pp. 3-7, Jan. 2006.

[16] T. M. Cover, *Elements of Information Theory*. New York: Wiley, 1991.

[17] M. S. Bazaraa, H. D. Sheral, and C. M. Shetty, *Nonlinear Programming: Theory and Algorithms*, 2nd ed. New York: John Wiley & Sons, 1993.

[18] A. J. Goldsmith and P. P. Varaiya, "Capacity of fading channels with channel side information," *IEEE Trans. Inform. Theory*, vol. 43, no. 6, pp. 1986-1992, Nov. 1997.

[19] J. S. Lee and L. E. Miller, *CDMA Systems Engineering Handbook*. Boston, MA: Artech House, 1998.

[20] Working Group 5 Evaluation Ad-Hoc Group, "1xEV-DV evaluation methodology - Addendum (V6)," Third Generation Partnership Project 2 (3GPP2), Contribution C50-20010820-026, July 2001.

[21] S. Chakravarty, R. Pankaj, and E. Esteves, "An algorithm for reverse traffic channel rate control for cdma2000 high rate packet data systems," in *Proc. IEEE Globecom*, Nov. 2001, pp. 3733-3737.

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