Resource Control for Elastic Traffic in CDMA Networks*

Vasilios A. Siris
Institute of Computer Science (ICS)
Foundation for Research and Technology - Hellas (FORTH)
P.O. Box 1385, GR 711 10, Heraklion, Crete, Greece
vsiris@ics.forth.gr

ABSTRACT

We present a framework for resource control in CDMA networks carrying elastic traffic, considering both the uplink and the downlink direction. The framework is based on microeconomics and congestion pricing, and seeks to exploit the joint control of the transmission rate and the signal quality in order to achieve efficient utilization of network resources, in a distributed and decentralized manner. An important feature of the framework is that it incorporates both the congestion for shared resources in wireless and wired networks, and the cost of battery power at mobile hosts. We prove that for elastic traffic, where users value only their average throughput, the user's net utility maximization problem can be decomposed into two simpler problems: one involving the selection of the optimal signal quality, and one involving the selection of the optimal transmission rate. Based on this result, the selection of signal quality can be performed as done today using outer loop power control, while rate adaptation can be integrated with rate adaptation at the transport layer.

Categories and Subject Descriptors

C.2.1 [**Computer-Communication Networks**]: Network Architecture and Design—*wireless communication, network communications*

General Terms

Algorithms, Design, Theory

Keywords

Congestion pricing, radio resource management, rate control, utility functions, wireless/wired integration

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1. INTRODUCTION

Procedures for efficient control and management of wireless network resources are becoming increasingly important. This is due to two factors: First, compared to fixed networks, there is a limited ability for increasing the capacity of mobile wireless networks. Second, emerging multimedia services and applications will increase the demand for bandwidth in wireless networks. Congestion pricing has been identified as a flexible framework for efficient and robust resource control in wired networks; e.g., see [8, 9, 2]. In this paper we investigate the application of microeconomic modelling and congestion pricing in Code Division Multiple Access (CDMA) wireless networks. Although our approach is generally applicable to CDMA-based systems, including systems utilizing a combination of code and time-division scheduling, we focus our discussion on Wideband CDMA.

WCDMA has emerged as the most widely adopted third generation (3G) air interface technology [6]. WCDMA is based on Direct Sequence CDMA (DS-CDMA), a spread spectrum technology where data bits are spread over the entire spectrum used for transmission, and unique digital codes are used to separate the signals from different mobiles; such an approach enables simpler statistical multiplexing, without the need for complex time or frequency scheduling. WCDMA supports variable bit rate transmission with the use of variable spreading factors and multiple codes; the former determines how much a data bit is spread in time. Finally, all the cells in a WCDMA network use the same frequency spectrum; this feature is behind the soft-capacity property of WCDMA networks, which results in the graceful degradation of performance as the load increases.

The goal of this paper is to present and investigate a new framework for resource control in CDMA networks, based on microeconomics and congestion pricing. The framework builds on results for resource usage, in both the uplink and the downlink, and seeks to exploit the joint control of the transmission rate and signal quality, the latter given by the bit-energy-to-noise-density ratio, in order to achieve economically efficient utilization of network resources, in a distributed and decentralized manner. An important feature of the framework is that it incorporates the congestion for shared resources in both wireless and wired networks, as well as the cost of battery power at the mobile hosts; hence, the framework can be the basis for the integration of resource control mechanisms in wireless and wired networks. We prove that for elastic traffic, where users value only their average throughput, the user's net utility maximization problem can be decomposed into two simpler problems:

one involving the selection of the optimal signal quality, and one involving the selection of the optimal transmission rate. Based on this result, the selection of signal quality can be performed as done today using outer loop power control, while rate adaptation can be integrated with rate adaptation at the transport layer.

Our work differs from other works, which we briefly discuss in Section 6, in one or more of the following points: First, our framework incorporates the congestion for both wireless and wired resources, in addition to the cost of battery power at mobile hosts. Second, our work considers the particular resource constraints in the uplink and downlink direction, identifying the differences in the resulting models. Third, in the uplink our approach does not differentiate mobile users based on their location. Finally, our work considers the joint optimization of the transmission rate and the signal quality, in order to achieve efficient resource utilization.

The paper is organized as follows. In Section 2 we summarize results concerning resource usage in CDMA networks. In Section 3 we present a framework, based on microeconomics and congestion pricing, for resource control in CDMA networks carrying elastic traffic. We begin with a simple model for the uplink and the downlink, which we then extend. In Section 4 we discuss the application of the above framework, identifying a number of practical issues. In Section 5 we present and discuss numerical investigations highlighting features of the proposed approach, including the difference of resource control in the uplink and in the downlink. In Section 6 we present a brief overview of related work, and in Section 7 we conclude the paper, identifying a number of related research issues we are currently investigating.

2. RESOURCE USAGE IN CDMA

Consider a single CDMA cell. Let W be the chip rate, which is fixed and equal to 3.84 Mcps for WCDMA. The bit-energy-to-noise-density ratio, E_b/N_0, at a receiver (either mobile host or base station) is given by [3, 22]

$$\left(\frac{E_b}{N_0}\right)_i = \frac{W}{r_i}\frac{g_i p_i}{I_i + \eta_i}\,, \tag{1}$$

where r_i is the transmission rate, p_i is the transmission power, g_i is the path gain between the base station and mobile i, I_i is the power of the interference, and η_i is the power of the background noise. The ratio W/r_i is the spreading factor or processing gain for mobile i. Due to the errors in the wireless network, the actual throughput (rate of successful data delivery) will be smaller than r_i.

The value of the bit-energy-to-noise-density ratio $(E_b/N_0)_i$ corresponds to the signal quality, since it determines the bit error rate, BER [3, 22]. Under the realistic assumption of additive white Gaussian noise, BER is a non-decreasing function of E_b/N_0, which depends on the multipath characteristics, and the modulation and forward error correction (FEC) algorithms. Let γ_i be the target bit-energy-to-noise-density ratio required to achieve a particular BER, or equivalently a particular frame error rate. This target is given to fast closed-loop power control, which adjusts the transmission power in order to achieve it. If we assume perfect power control, then $(E_b/N_0)_i = \gamma_i$.

When a sender does not send data continuously, the average E_b/N_0 requirements will be met, if the right hand-side of (1) is multiplied by the percentage of time the sender is 'on', actually transmitting data; this percentage, called activity factor, is 0.67 for voice.

2.1 Resource Usage in the Uplink

In the uplink, the interference I_i for mobile i is the sum of the power of the signals received by the base station from all other mobile hosts, i.e., $I_i = \sum_{j\neq i} g_j p_j$. Moreover, we can assume that the background noise at the base station is the same for all mobiles, i.e., $\eta_i = \eta$. If γ_i is the target bit-energy-to-noise-density ratio, then under perfect power control $(E_b/N_0)_i = \gamma_i$, and (1) becomes

$$\gamma_i = \frac{W}{r_i}\frac{g_i p_i}{\sum_{j\neq i} g_j p_j + \eta}\,. \tag{2}$$

Solving the set of equations given by (2) for each mobile i, we get [22, 16]

$$g_i p_i = \frac{\eta \alpha_i^{\mathrm{UL}}}{1 - \sum_j \alpha_j^{\mathrm{UL}}}\,, \tag{3}$$

where the load factor α_i^{UL} is given by

$$\alpha_i^{\mathrm{UL}} = \frac{1}{\left(\frac{W}{r_i\gamma_i} + 1\right)}\,. \tag{4}$$

Note that the power levels given by the set of equations (3) for $i \in I$, where I is the set of mobiles, are the minimum such that the target bit-energy-to-noise-density ratios $\{\gamma_i\}$ are met. Since the power p_i can take only positive values, from (3) we get

$$\sum_i \alpha_i^{\mathrm{UL}} < 1\,. \tag{5}$$

The last equation illustrates that the uplink is *interference-limited*: Even when they have no power constraints, mobile hosts cannot increase their power without bound, due to the increased interference they would cause to the other mobiles. If (5) is violated, then the target $\{\gamma_i\}$ cannot be met for all mobiles.

Equation (5) suggests that α_i^{UL} is a measure of the resource usage, or the *effective usage*, of a mobile host i in the uplink direction. From Equation (4), we conclude that resource usage in the uplink of CDMA networks is an increasing function of the product of two parameters, which can be controlled *independently*: the transmission rate r_i and the signal quality, expressed in terms of the target bit-energy-to-noise-density ratio γ_i.

If each mobile uses a small portion of the wireless resource, which is the case when there is a large number of mobile users, then we have $\frac{W}{r_i\gamma_i} \gg 1$, hence $\alpha_i^{\mathrm{UL}} \approx \frac{r_i\gamma_i}{W}$ and the resource constraint given by Equation (5) can be approximated by

$$\sum_i r_i\gamma_i < W\,. \tag{6}$$

The above results assumed that there are no constraints on a mobile's maximum transmission power. They can be extended to include such constraints [16]. Moreover, the interference from neighboring cells can be taken into account by considering the intercell interference coefficient, which gives the ratio of the interference from neighboring cells over the intracell interference [3].

2.2 Resource Usage in the Downlink

In the downlink, the interference for mobile i is $I_i = \theta_i g_i \sum_{j \neq i} p_j$, where θ_i represents the orthogonality of the codes used in the downlink. If γ_i is the target signal quality for mobile i, and assuming as above that we have perfect power control, then (1) becomes

$$\gamma_i = \frac{W}{r_i} \frac{g_i p_i}{\theta_i g_i \sum_{j \neq i} p_j + \eta_i} . \tag{7}$$

The orthogonality factor θ_i depends on multipath effects, hence can be different for different mobile hosts. Typical values fall in the range $[0.1, 0.6]$, see [6, p. 163].

In the downlink, unlike the uplink, there is a limit on the total transmission power[1], say $\bar{p}$, hence the downlink is *power-limited*. The corresponding resource constraint is

$$\sum_i p_i \leq \bar{p} . \tag{8}$$

The last equation suggests that the transmission power from the base station characterizes resource usage in the downlink direction.

3. RESOURCE CONTROL BASED ON CONGESTION PRICING

In this section we first propose a utility function that is appropriate for elastic traffic in wireless networks; utility functions are widely used for capturing user and application requirements, and give the level of satisfaction for a given level of service. Then, based on the results for resource usage of the previous section, we present and investigate congestion pricing models for the uplink and the downlink in CDMA networks.

We consider the case of elastic (best-effort) traffic, where users value only the average throughput of successful data transmission. This throughput is the product of the transmission rate and the probability of successful packet transmission. The latter is a function of the bit error rate *BER*, which as discussed in Section 2 is a function of the target bit-energy-to-noise-density ratio γ. Hence, the probability of successful packet transmission can be written as $P_s(\gamma)$, in which case the average throughput is $rP_s(\gamma)$ [13, 4]. Thus, the utility for elastic traffic where users value only their average throughput has the form

$$U\left(rP_s(\gamma)\right) .$$

If the mobile user does not have minimum rate requirements, then his utility is typically concave. On the other hand, if the user has minimum rate requirements, equivalently maximum delay requirements, then his utility has a sigmoid shape.

Let $c(r_i, \gamma_i, p_i)$ be the charge incurred by user i with rate r_i, target bit-energy-to-noise-density ratio γ_i, and transmission power p_i. The user's net utility maximization problem has the following general form (for simplicity, we assume that all users have the same packet success probability):

$$\begin{array}{ll} \text{maximize} & U_i\left(r_i P_s(\gamma_i)\right) - c(r_i, \gamma_i, p_i) \\ \text{over} & r_i \geq 0, \gamma_i \geq 0 \, , \end{array} \tag{9}$$

where the variables r_i, γ_i, p_i are related through Equation (2) or (7), for the uplink or the downlink direction respectively. The charge $c(r_i, \gamma_i, p_i)$ can include both the congestion charge for shared resources in the wireless network and, as we discuss in Section 3.2, the congestion charge for resources in the wired network and the cost of battery power at the mobile host. Specific formulations for the uplink and downlink, based on the results of the previous section regarding resource usage in each direction, will be discussed in the following subsections.

The optimization in (9) involves two parameters: the transmission rate r_i and the target bit-energy-to-noise-density ratio γ_i. An important result that we prove in Section 3.1 for the uplink, but which also holds for more general forms of the charge function $c(\cdot)$, is that the user's net utility maximization problem can be decomposed into two subproblems: one involving the selection of the optimal γ^*, which depends only on the packet success probability $P_s(\gamma)$, and one involving the selection of the optimal rate r_i^*, which depends on the user's utility and charge.

3.1 Congestion Pricing for the Uplink

In this section we consider the uplink, and first assume there is a large number of mobiles, each using a small portion of the wireless resource. Note, however, that the results for this simple case also hold for the more general case. The wireless resource constraint is given by (6)

$$\sum_i r_i \gamma_i < W .$$

To provide the right incentives for efficient use of network resources, user i's charge should be proportion to his resource usage, which is given by $r_i\gamma_i$. Hence, in the uplink the user optimization problem (9) becomes

$$\begin{array}{ll} \text{maximize} & U_i\left(r_i P_s(\gamma_i)\right) - \lambda r_i \gamma_i \\ \text{over} & r_i \geq 0, \gamma_i \geq 0 \, , \end{array} \tag{10}$$

where λ is the shadow price for resource $r_i\gamma_i$.

In the above model, prices are independent of the mobile's position. This is because the uplink is interference-limited, and interference depends on the *received* power at the base station. In this respect our approach differs from the work of [4, 17, 21], where charges depend on the *transmitted* power; such a dependence results in mobile users that are far from the base station to incur a higher charge, for the same rate and signal quality, compared to users close to the base station. On the other hand, as we discuss in Section 3.3, in the downlink a mobile's position influences the charge, since resource usage in this case is determined by the *transmitted* power from the base station.

3.1.1 Properties of the optimal solution

An important property which greatly simplifies the application of (10) is that the optimal γ_i^* of the target bit-energy-to-noise-density ratio is independent of both the price λ and the user's utility. This allows the decoupling of the two problems of selecting the optimal γ_i^* and the optimal transmission rate r_i^*. This property is stated and proved in the following proposition.[2]

[1] $\bar{p}$ refers to the total power the base station can transmit minus the power used for the downlink control channels.

[2] We include only the proof for the first Proposition. The other proofs can be found in [18].

PROPOSITION 1. *Let $U_i(x_i)$ and $P_s(\gamma_i)$ be continuously differentiable functions of the throughput $x_i = r_i P_s(\gamma_i)$ and the target bit-energy-to-noise-density ratio γ_i, respectively. Also assume that $U_i'(x_i) > 0$ for all $x_i \geq 0$. If there exists $r_i^* > 0$ and $\gamma_i^* > 0$ that achieve the maximum of (10), then γ_i^* is independent of the price λ and the utility, and satisfies*

$$P_s(\gamma_i^*) = P_s'(\gamma_i^*)\gamma_i^* \,. \tag{11}$$

PROOF. At the optimal, the partial derivatives of (10) with respect to r_i and γ_i are zero, hence

$$\begin{aligned} \frac{\vartheta U_i(r_i P_s(\gamma_i^*))}{\vartheta r_i} &= \lambda\gamma_i^* \Rightarrow \\ U_i'(x_i^*)\frac{\vartheta(r_i P_s(\gamma_i^*))}{\vartheta r_i} &= \lambda\gamma_i^* \Rightarrow \\ U_i'(x_i^*)P_s(\gamma_i^*) &= \lambda\gamma_i^* \end{aligned} \tag{12}$$

and

$$\begin{aligned} \frac{\vartheta U_i(r_i^* P_s(\gamma_i))}{\vartheta \gamma_i} &= \lambda r_i^* \Rightarrow \\ U_i'(x_i^*)\frac{\vartheta(r_i^* P_s(\gamma_i))}{\vartheta \gamma_i} &= \lambda r_i^* \overset{r_i^*>0}{\Rightarrow} \\ U_i'(x_i^*)P_s'(\gamma_i^*) &= \lambda \end{aligned} \tag{13}$$

From (12) and (13) we get (11). □

Proposition 1 can be proved for the more general case where the charge has the form $c(r\gamma)$ or $c(rP_s(\gamma))$. Interestingly, the extensions to the basic model given by (10) that we discuss in Section 3.2, and the net utility maximization problem for the downlink that we discuss in Section 3.3, are of this form.

An interesting observation is that the optimal γ_i^*, in the case $\gamma_i^* > 0$, that satisfies (11) also maximizes the number of bits successfully received per unit of energy [4]:

$$\max_{\gamma_i>0} \frac{r_i P_s(\gamma_i)}{p_i} \,,$$

since substituting (2) in the last equation gives

$$\max_{\gamma_i>0} \frac{W}{I_i+\eta}\frac{P_s(\gamma_i)}{\gamma_i} \,,$$

which is maximized for γ_i^* satisfying (11). This last observation indicates that the optimal γ_i^* that maximizes the net utility in (10), also maximizes the number of bits successfully received per unit of energy. Moreover, under the assumptions of Proposition 1, this result is independent of the user's utility and the congestion price, and can be achieved in a decentralized manner via pricing. Finally, we note that (11) also holds when the objective is to maximize the total throughput [13].

The next proposition is related to the existence of a $\gamma_i^* > 0$. For simplicity we drop the subscript i, since the optimal target bit-energy-to-noise-density ratio will be the same for mobiles with the same dependence of the packet success probability on γ.

PROPOSITION 2. *Assume that $P_s(\gamma)$ is continuously differentiable, and is strictly convex for $\gamma < \gamma^0$ and strictly concave for $\gamma > \gamma^1$. Also assume that $P_s(0) = 0$. Then there exists $\gamma^* > 0$ that satisfies (11). Moreover, if $\gamma^0 = \gamma^1$, then γ^* is unique.*

In practise, we can have $P_s(0) > 0$, i.e., the packet success probability does not tend to zero as γ tends to zero; $\gamma = 0$, hence $p = 0$, corresponds to the case where the receiver is *guessing* what the bits transmitted by the sender are [4]. However, as we see next, $P_s(0)$ will typically be very small, and γ^* satisfying (11) will exist.

In the case of additive white Gaussian noise and a non-fading channel, the bit error rate for DPSK (Differential Phase Shift Keying) modulation is [15]

$$BER(\gamma) = 0.5e^{-\gamma} \,.$$

From the last equation, observe that $BER(0) > 0$. If there is no error correction, and bit errors are independent and are all detected, then the packet success probability $P_s(\gamma)$ is given by

$$P_s(\gamma) = (1 - BER(\gamma))^L \,, \tag{14}$$

where L is the number of bits in one packet. For $L = 60$ bits, the last equation gives $P_s(0) = 8.710^{-19}$.

When up to k bit errors are correctable, the packet success probability can be approximated by

$$P_s(\gamma) = \sum_{j=0}^{k} \binom{L}{j} BER(\gamma)^j (1 - BER(\gamma))^{L-j} \,. \tag{15}$$

Figure 1(a) shows the packet success probability with no error correction, which is computed from Equation (14). Observe that $P_s(\gamma)$ has a sigmoid shape, and a unique γ^* satisfying (11) exists. Indeed, γ^* corresponds to the tangent of the line passing through the origin with the curve $P_s(\gamma)$. Figure 1(b) shows that in the presence of forward error correction (FEC), in which case the packet success probability is computed from Equation (15), a unique γ^* again exists; moreover, γ^* in the presence of FEC is smaller than when there is no FEC; γ^* is also smaller in the case of BPSK and QPSK modulation, in which case the bit error rate is [15]

$$BER(\gamma) = 0.5\mathrm{erfc}(\sqrt{\gamma}) \,,$$

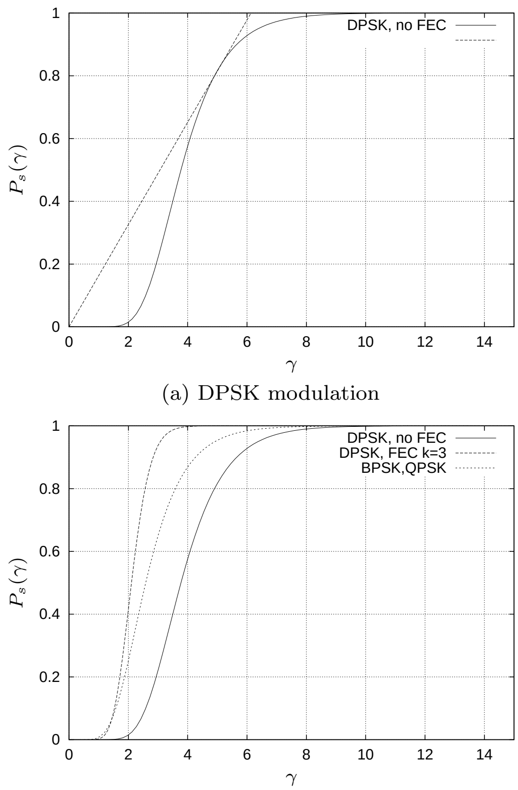
where erfc is the complementary error function.

The optimality of γ^* is stated in the following two propositions. The proof for the latter uses Propositions 1, 3, and Theorem 1 in [8].

PROPOSITION 3. *Let γ_i^* be the unique value satisfying (11), and assume $P_s''(\gamma_i^*) < 0$. If the utility $U_i(x_i)$ in (10) is differentiable and strictly concave and $U_i'(x_i) > 0, \forall x_i > 0$, where $x_i = r_i P_s(\gamma_i)$, then there exists a r_i^*, that along with γ_i^* achieves the maximum in (10).*

PROPOSITION 4. *Under the conditions stated in Propositions 1 and 3, and if $U_i(x_i)$ is increasing and strictly concave in $x_i = r_i P_s(\gamma_i)$, then there exists a price λ such that the allocations $\{(r_i, \gamma_i)\}$ formed from the unique solutions (r_i, γ_i) to (10) maximize the network revenue*

$$\begin{aligned} &\textit{maximize} && \sum_i \lambda r_i \gamma_i \\ &\textit{over} && r_i \geq 0, \gamma_i \geq 0 \\ &\textit{subject to} && \sum_i r_i \gamma_i < W \,, \end{aligned}$$



(a) DPSK modulation

(b) DPSK with FEC and BPSK/QPSK

Figure 1: Packet success rate for DPSK modulation with 60 bits long packets, with and without error correction, and for BPSK/QPSK modulation. The optimal $\gamma^*(\approx 5)$ satisfies (11), and is the value of γ at which the line passing through the origin is tangent to $P_s(\gamma)$.

and the social welfare

$$\begin{aligned} \textit{maximize} \quad & \sum_i U_i(r_i P_s(\gamma_i)) \\ \textit{over} \quad & r_i \geq 0, \gamma_i \geq 0 \\ \textit{subject to} \quad & \sum_i r_i \gamma_i < W\,. \end{aligned}$$

Due to Propositions 1 and 3, the user optimization problem in (10) can be reduced to

$$\begin{aligned} \text{maximize} \quad & U_i(r_i P_s(\gamma^*)) - \lambda r_i \gamma^* \\ \text{over} \quad & r_i \geq 0\,, \end{aligned} \tag{16}$$

with γ^* satisfying (11). In the case of a strictly concave utility, the optimal r_i^* is given by

$$r_i^* = \frac{1}{P_s(\gamma^*)} U_i'^{-1}\left(\frac{\lambda\gamma^*}{P_s(\gamma^*)}\right)\,. \tag{17}$$

Assume now that the utility is not a strictly concave function of the rate, but has a sigmoid shape and is bounded by the line ξr, which is tangent to the utility $U_i(r_i P_s(\gamma^*))$ at rate r_i^0, after which the utility is strictly concave. In this case, the optimal rate r_i^* is given by (17) if and only if $r_i^* \geq r_i^0$. If this inequality does not hold, then the optimal rate is zero. In this case, γ^* can take any value, since both the utility and the charge is zero (Equation (11) need not hold in this case).

3.2 Extensions

In this section we consider extensions to the basic model corresponding to (10). For all extensions, Propositions 1-3 hold, hence the corresponding user optimization problems can be reduced to a form similar to (16) and (11).

3.2.1 *Small number of mobile hosts*

If the number of mobile hosts is not large, then the resource constraint is given by (5) rather than its approximation (6), and the user optimization problem becomes

$$\begin{aligned} \text{maximize} \quad & U_i(r_i P_s(\gamma_i)) - \lambda \alpha_i^{\text{UL}} \\ \text{over} \quad & r_i \geq 0, \gamma_i \geq 0\,, \end{aligned}$$

with α_i^{UL} given by (4).

3.2.2 *Including the cost of battery power*

The cost of battery power can be included by adding an appropriate term to (10). For example, if the battery cost is linear to the power, we have

$$\begin{aligned} \text{maximize} \quad & U_i(r_i P_s(\gamma_i)) - \lambda r_i \gamma_i - \nu_i p_i \\ \text{over} \quad & r_i \geq 0, \gamma_i \geq 0\,, \end{aligned}$$

where p_i is the transmitted power and ν_i is the cost per unit of battery power, which can be different for different users.

3.2.3 *Integration with transport layer congestion control*

The congestion cost associated with the fixed network can be taken into account by modifying (10) to

$$\begin{aligned} \text{maximize} \quad & U_i(r_i P_s(\gamma_i)) - \lambda r_i \gamma - \mu r_i P_s(\gamma_i) \\ \text{over} \quad & r_i \geq 0, \gamma_i \geq 0\,, \end{aligned} \tag{18}$$

where μ is the congestion price for resources in the fixed network. Observe that the congestion charge for the fixed network is proportional to the rate of successful data transfer over the wireless network, i.e., $r_i P_s(\gamma_i)$. Equation (18) can be the basis for integrated rate control over wireless and wired resources. We will discuss in Section 4.1 one possible approach for using the same signalling mechanism for conveying congestion information in both networks.

3.2.4 *Bound on the total interference produced by elastic traffic*

The network might wish to limit the total interference that elastic traffic causes to other types of traffic, such as real-time traffic, to be p_{max}. In this case, the target function in the user problem (10) remains the same, but the constraint (6) changes to

$$\sum_j g_j p_j \leq p_{max}\,.$$

3.3 Congestion Pricing for the Downlink

The capacity constraint in the downlink is in terms of the maximum power $\bar{p}$ that the base station can transmit (8):

$$\sum_i p_i \leq \bar{p}\,.$$

Hence, it is appropriate for the network to charge user i in proportion to his power p_i. In this case, the user optimization problem becomes

$$\begin{aligned} \text{maximize} \quad & U_i\left(r_i(P_s(\gamma_i))\right) - \lambda p_i \\ \text{over} \quad & r_i \geq 0, \gamma_i \geq 0\,, \end{aligned} \tag{19}$$

where λ is the price per unit of power, and the variables r_i, γ_i, and p_i are related through (7).

Propositions 1 - 3 also hold for the downlink. On the other hand, note that Proposition 4 does not hold. Due to Propositions 1 and 3 the user optimization problem in (19), combined with (7), can be reduced to

$$\begin{aligned} \text{maximize} \quad & U_i(r_i P_s(\gamma^*)) - \lambda \frac{r_i \gamma^* (I_i + \eta_i)}{W g_i} \\ \text{over} \quad & r_i \geq 0\,, \end{aligned} \tag{20}$$

with γ^* satisfying (11), and $I_i = \theta_i g_i \sum_{j \neq i} p_j$. In the case of a strictly concave utility, the optimal r_i^* is given by

$$r_i^* = \frac{1}{P_s(\gamma^*)} {U_i'}^{-1} \left(\frac{\lambda \gamma^* (I_i + \eta_i)}{W g_i P_s(\gamma^*)} \right) . \tag{21}$$

In the above model, unlike the case for the uplink, mobile users that are far from the base station incur a higher charge, for the same rate and target bit-energy-to-noise-density ratio. As a result, for the same utility, users far from the base station will send at a lower transmission rate, compared to users close to the base station; related investigations are presented in Section 5. In the downlink, the dependence of charges on a mobile's distance results in more efficient utilization of the base station's power, since it leads to higher aggregate utility.

4. APPLICATION OF THE FRAMEWORK

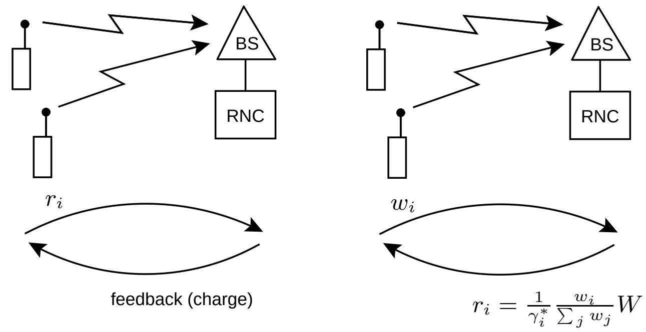
In this section we discuss the application of the framework presented in the previous section, highlighting some important practical considerations. In particular, we discuss two alternatives for applying the proposed framework: The first involves direct communication of prices from the base station/radio network controller (BS/RNC) to the mobile hosts (MHs), which respond by selecting the transmission rate that maximizes their net utility. The second involves communication of *willingness-to-pay* or weight values from the mobile users to the RNC, which allocates rates according to these values. The above two alternatives are similar to the two decompositions of the model for rate control of elastic traffic in fixed networks that is investigated in [8].

4.1 Procedure with explicit communication of prices

4.1.1 Uplink

We first describe the procedure for applying the congestion pricing model for the uplink, presented in Section 3.1, when there is direct communication of prices from the base station/radio network controller (BS/RNC) to the mobile hosts (MHs), Figure 2(a). The procedure involves the following steps:

1. For each MH i, the RNC selects the optimal γ_i^* based on (11).
2. The RNC announces the price per unit of wireless resource λ.



(a) direct price feedback (b) willingness-to-pay

Figure 2: With direct price communication (left figure), a mobile responds to price feedback by adjusting its transmission rate. On the other hand, with the willingness-to-pay approach (right figure), the willingness-to-pay can be adjusted over longer timescales. The first approach results in more efficient behavior, but requires more complex functionality in the mobile compared to the second approach.

3. Each MH i selects its rate r_i^* based on (16).
4. The RNC charges MH i by $\lambda r_i^* \gamma_i^*$.
5. The RNC adjusts price λ based on the load, and goes to Step 2.

In WCDMA, the procedure for selecting γ (target E_b/N_0) is performed at the RNC, during outer loop power control: The BS measures the bit error rate *BER* (or the frame error rate *FER*), and sends the measurement to the RNC, which adjusts γ to achieve a particular *BER*; γ is then used as the target for fast closed-loop power control, which operates between the base station and the mobiles. Hence, it is appropriate to perform the selection of the optimal γ_i^* in Step 1 at the RNC, effectively replacing the normal outer loop power control procedure. Moreover, γ_i^* will change whenever the dependence of the packet success probability on γ changes, e.g., when the multipath characteristics change.

Assuming all mobiles have the same packet success rate, they will have the same optimal γ^* that satisfies (11). Given the sigmoid shape[3] of $P_s(\gamma)$ in Figure 1, γ^* can be found by gradually increasing γ while the derivative $P_s'(\gamma)$ is larger than $P_s(\gamma)/\gamma$, and decreasing it when the derivative is smaller. The above procedure is similar to the typical procedure used for outer loop power control today [6, p. 196-200], hence the latter would require small modifications in order to select the target bit-energy-to-noise-density ratio based on (11). On the other hand, if the packet success rate is different for different mobiles, then the optimal γ_i^* would be different for different mobiles; note that in all cases γ_i^* would satisfy (11).

As noted above, γ^* is the target for fast closed-loop power control between the base station and the mobile hosts; this power control loop operates on a much faster timescale compared to the timescale over which the transmission rate is adjusted. Indeed, in WCDMA fast closed-loop power control operates at a frequency of 1500 Hz, resulting in one

[3] The fact that $P_s(0) > 0$ will not be a problem in practise since, as our numerical results show, $P_s(0)$ will typically be very small.

power update approximately every 0.67 milliseconds. On the other hand, the rate remains constant within a single frame, whose minimum duration is 10 milliseconds. Hence, the rate control procedure in Step 3 works on slower timescales compared to the timescales of fast closed-loop power control. Moreover, observe from Equation (2) that a change in the transmission rate would require adjusting the transmission power in order to maintain the same γ^*.

In Step 4, charges are proportional to the product $r_i^* \gamma_i^*$. The BS/RNC, assuming perfect error detection, can estimate the transmission rate r_i^* from the received rate. Also, the BS/RNC knows γ_i^*. Hence, there is no parameter that the mobile user can falsely declare in order to reduce his charge, without reducing his level of service.

Step 5 involves adjusting the price λ based on some estimate of the level of congestion of wireless network resources. The specific procedure for adjusting the price is related to how prices are communicated to the mobile users. One alternative is to have the RNC directly announce prices; this requires a new control channel from the RNC to the MHs. The price function is of the form $\lambda(\rho) : [0,1] \to [0,\infty]$. The function that we consider in our numerical investigations is

$$\lambda(\rho) = \frac{\phi}{1-\rho}\,, \tag{22}$$

where ϕ can be adjusted to achieve a target utilization, if a rough estimate of the demand (number of users and their utilities) is known.

Another option is to consider the same signalling channel to convey congestion information for both wireless and wired network resources; the corresponding model is given by (18). An interesting approach is to have the congestion signals for both types of networks communicated using Explicit Congestion Notification (ECN) [14], which has been approved as an IETF proposed standard. The possible use of ECN marking in wireless networks has been proposed by other researchers, e.g., see [11], but with the objective of improving the performance of TCP over wireless links.

ECN marking for conveying congestion information related to the wireless network can be performed at the RNC, whereas in the wired network routers are responsible for packet marking. Indeed, the RNC would be responsible for packet marking in both the uplink and the downlink, based on the level of congestion in each direction. Such a selection is appropriate, since the RNC is responsible for managing radio resources, and performs admission control and transmission scheduling. One challenging issue is that in the uplink there is no shared buffer, hence queue-dependent marking schemes, such as Random Early Detection (RED), cannot be applied. Instead, marking can depend solely on the average load of the wireless channel.

Both the above two alternatives require estimation of the load ρ. One approach for measuring the load involves direct application of $\sum_i \alpha_i^{\mathrm{UL}}$, with α_i^{UL} given by (4). A more efficient method is to use aggregate measurements of the total interference I_{total} (which includes the noise), and the noise η, from which the total load can be estimated from the following equation, which can be derived by summing (3) for all mobiles (this sum is called uplink load factor, [6, p. 160-162]):

$$\sum_j \alpha_j^{\mathrm{UL}} = \frac{I_{total} - \eta}{I_{total}}\,. \tag{23}$$

Advantages of using the last equation are that only aggregate power measurements are required and the interference of neighboring cells is implicitly handled.

4.1.2 Downlink

The procedure for applying the congestion pricing model for the downlink, presented in Section 3.3, involves similar steps as those in the uplink, with the modifications that we describe next.

The selection of the optimal bit-energy-to-noise-density ratio γ_i^*, as in the uplink, is based on (11), but is performed at the mobile hosts. The selection of the rate r_i^* in Step 3 is based on (20). Note that the path gain and interference in this equation can change on a fast timescale. Since, as discussed in the previous subsection, our rate control procedure operates on slower timescales, the values of I_i and g_i that appear in (20) can be taken to be averages. Moreover, the interference and the noise can be directly measured at the mobile host, whereas the path gain can be estimated using the received power of the downlink pilot channel [6].

The charge in Step 4 is proportional to the average transmission power $\tilde{p}_i$. Finally, the price adjustment in Step 5 can follow a similar function as (22), with the difference that now the load is given by

$$\frac{\sum_i \tilde{p}_i}{\bar{p}}\,,$$

since the resource constraint in the downlink, Equation (8), is in terms of the total transmission power at the base station.

4.2 Allocation of rates by RNC according to willingness-to-pay

An alternative to the approach discussed in the previous subsection, that involves communication of prices from the base station to the mobile hosts and rate adaptation by the mobile hosts, is to add more intelligence to the RNC, to allocate rates according to the users' declared willingness-to-pay or weight values, Figure 2(b). Indeed, this approach is similar to the class-based quality of service framework presented in [5].

The above approach is attractive for the following reasons: i) WCDMA supports negotiation of bearer service properties both at call setup, and during a call [6, p. 10]; ii) the RNC already has intelligence for supporting flexible packet scheduling and load control; iii) cellular radio networks are single hop networks[4], hence the approach we describe satisfies desirable fairness properties, namely proportional fairness [8]; and iv) the approach is less demanding for mobile hosts, which do not need to adjust their rate in the (relatively fast) timescale over which the congestion price changes, but rather adjust their willingness-to-pay on a slower timescale. Due to all the above, rate allocation according to willingness-to-pay values require fewer modifications to existing procedures in WCDMA systems, compared to the explicit price communication approach described in the previous subsection, hence is easier to implement. On the other hand, the explicit price communication approach places more intelligence and control at the mobile user, and

[4] Achieving similar fairness objectives in a multiple hop network, with rate allocation done by the routers, is more complicated.

can support the integration of congestion control in wireless and wired networks; support of such integration with a willingness-to-pay like scheme is not straightforward.

4.2.1 Uplink

The scheme for the uplink works as follows: Mobile users communicate their willingness-to-pay to the RNC, which then allocates rates in proportion to the declared willingness-to-pay values. In particular, the rate for user i is given by

$$r_i = \frac{1}{\gamma_i^*}\frac{w_i}{\sum_j w_j}W\,, \tag{24}$$

where w_i is the willingness-to-pay for user i and γ_i^* satisfies (11). Observe from the last equation that a user's rate is inversely proportional to his target bit-energy-to-noise-density ratio γ_i^*. Also note that in this approach the rate r_i needs to be signaled from the RNC to the mobile i.

The approach for rate allocation based on willingness-to-pay values corresponds to the case where users have a logarithmic utility $U_i(r_i P_s(\gamma_i)) = w_i \log(r_i P_s(\gamma_i))$. Substituting this utility in Equation (10), and taking the derivative with respect to r_i, we find that a user's net utility is maximized for $w_i = \lambda r_i \gamma_i^*$, where as before γ_i^* satisfies (11); hence w_i represents a price per unit of time, which justifies the term 'willingness-to-pay'. From the above we see that user i's resource usage $r_i\gamma_i$ is proportional to his willingness-to-pay, which leads to the proportional allocation of resources in Equation (24).

For a general form of the utility function, and if updates of the willingness-to-pay can occur in intervals of fixed duration τ, then the user can vary his willingness-to-pay according to $w_i(t) = \hat{\lambda}(t)\gamma_i^* r_i^*(t)$, where $r_i^*(t)$ and γ_i^* are given by (17) and (11) respectively, and $\hat{\lambda}(t)$ is an estimate of the price; e.g., $\hat{\lambda}(t) = \frac{w_i(t-\tau)}{r_i(t-\tau)\gamma_i^*}$, where $r_i(t-\tau)$ is the rate allocated to user i at time $t-\tau$.

4.2.2 Downlink

In the downlink, similar to the uplink, users declare their willingness-to-pay to the RNC. Based on these declarations, the average power allocated to mobile i is

$$\tilde{p}_i = \frac{w_i}{\sum_j w_j}\bar{p}\,.$$

From $\tilde{p}_i$, and using (7), the RNC allocates to mobile i the rate

$$r_i = \frac{W}{\gamma_i^*}\frac{g_i}{I_i + \eta_i}\frac{w_i}{\sum_j w_j}\bar{p}\,,$$

where similar to the uplink, γ_i^* is determined from (11). Hence, the above approach requires the RNC to have knowledge of the average path gain, the average interference, the noise, and the target bit-energy-to-noise-density ratio. Although WCDMA supports the reporting of such parameters to the RNC [6], care must be taken to ensure truthful declaration from the mobile hosts; for example, truthful declaration can be ensured if the software running in the mobile hosts, which is responsible for reporting the above parameters, cannot be modified by users.

5. NUMERICAL INVESTIGATIONS

In this section we present numerical investigations that demonstrate the application of our framework and how variables such as the rate, the signal quality, and the charge in the steady state depend on a mobile's distance and the wireless network's load; moreover, we identify and explain the differences between the uplink and the downlink resource control models.

Table 1: Parameters for the numerical investigations. d is distance in Km.

parameter	value
total BS power, $\bar{p}$	16.7 Watt
load	60%
noise, η	10^{-13} Watt
path gain, $g(d)$	kd^{-u}, $u = 3.52$, $k = 1.82 \cdot 10^{-14}$
downlink orthogonality, θ	0.1
$BER(\gamma)$ (DPSK)	$0.5e^{-\gamma}$
bits per pkt, L	60
γ^*, from (11) & Fig. 1(a)	5
utility, concave	$1 - e^{-bx}$, $b = 0.4$
utility, sigmoid	$1 - e^{-b(x-x_0)}$, $x \geq 5.6P_s(\gamma^*)$ $1 - e^{-bx}$, $x < 5.6P_s(\gamma^*)$ $b = 0.4, x_0 = 2$

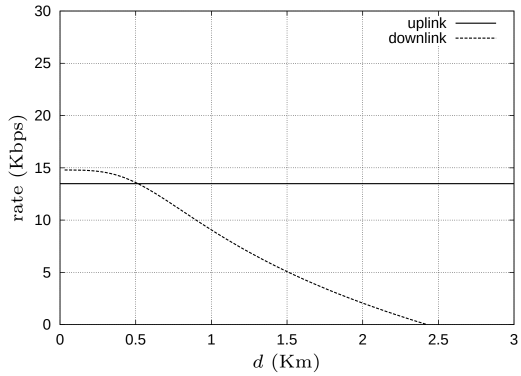
The rate for the uplink is computed from (10) and for the downlink from (19). In both cases, γ^* is determined from (11). We consider two types of utility curves: concave and sigmoid. The parameters for the particular functions, along with the propagation model and other system parameters are shown in Table 1.

Figure 3(a) shows that in the uplink, the rate is independent of a mobile's distance from the base station. This is expected, since congestion charges are also independent of the distance, and depend only on the transmission rate and the target bit-energy-to-noise-density ratio. On the other hand, in the downlink, the optimal rate that maximizes a user's net utility decreases with the distance. This is due to the dependence of charges on the *transmitted* power from the base station, which results in the rate depending on the path gain, as evident from Equation (21).

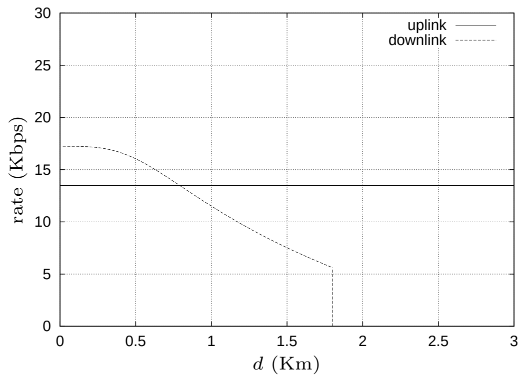
Figure 3(b) is for the case where users have a sigmoid utility. The results for the uplink remain the same. On the other hand, the results for the downlink are different. In particular, there is a distance where the optimal rate drops abruptly to zero; this is the distance after which the net utility becomes negative for any positive rate, hence the user benefits most by not sending data.

Figure 4(a) shows the corresponding power requirements for the uplink and the downlink, in the case of a concave utility. In the uplink, charges are independent of the mobile's position and its transmission power, hence the power continuously increases with the distance in order to maintain a constant signal quality. In the downlink, the power initially increases with the distance, since doing so increases the net utility; at some distance, the power decreases with the distance, since the path loss increases fast with the distance, hence the necessary power and the corresponding charge, which is proportional to the power, increase fast.

Figure 4(b) shows the results for a sigmoid utility. There is a difference only for the downlink, where the power drops to zero after some distance, when the net utility is negative for any positive rate, hence the net utility is maximized, and equals zero, for zero rate and power.

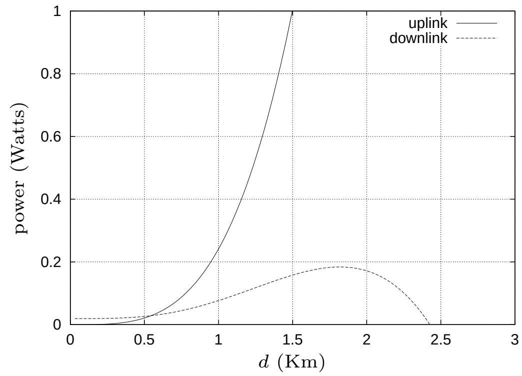


(a) Concave utility

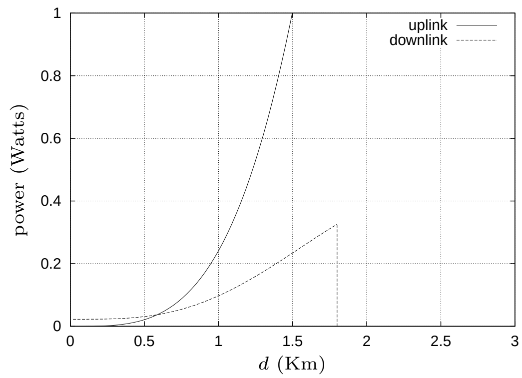


(b) Sigmoid utility

Figure 3: In the uplink, the optimal rate is independent of the distance, and in the downlink it decreases with the distance. For a sigmoid utility, in the downlink the rate drops to zero after some distance, when the net utility is negative for any positive rate.



(a) Concave utility



(b) Sigmoid utility

Figure 4: In the uplink, the power increases with the distance, to maintain a constant signal quality. In the downlink, the power initially increases, and then decreases. For a sigmoid utility, in the downlink the rate drops to zero after some distance, when the net utility is negative for any positive rate.

Figures 5(a) and 5(b) show the dependence of the charge on the distance. As expected, for the uplink the charge is independent of the distance. On the other hand, for the downlink, the dependence of the charge on the distance is similar to the dependence of the power on the distance, since in the downlink the charge is proportional to the power.

The dependence of the rate and the power on the load, for a concave utility, and for the uplink and downlink are shown in Figures 6(a) and 6(b). For the uplink, the load is taken to be $\sum_j \alpha_j^{\text{UL}} \approx \sum_j r_j\gamma_j/W$, and for the downlink $\sum_j \tilde{p}_j/\bar{p}$. Figure 6(a) shows that the rate decreases faster with the load in the downlink. The reason for this behavior is that the rate in the downlink, as (21) shows, depends on the load both through the congestion price and through the interference.

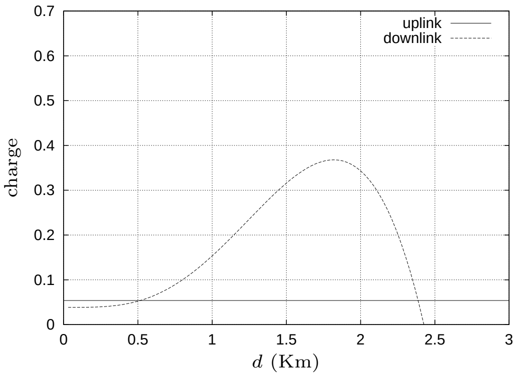
Figure 6(b) shows that in the uplink the power increases with the load. On the other hand, in the downlink the power initially increases and then decreases. This difference is due to the following: The power depends on both the rate and the interference, Equation (1). The dependence of the rate on the load is shown in Figure 6(a). In the uplink the interference increases fast with the load, since from (23) we have $I_i + \eta \approx I_{total} = \eta/(1-\rho)$. On the other hand, in the downlink the interference has an almost linear dependence on the load, since $I_i + \eta_i = \theta_i g_i \sum_{j\neq i} p_j + \eta_i \approx \theta_i g_i \rho\bar{p} + \eta_i$. Both the above two approximations are for the case of a large number of mobile users, each contributing a small percentage to the total interference.

6. RELATED WORK

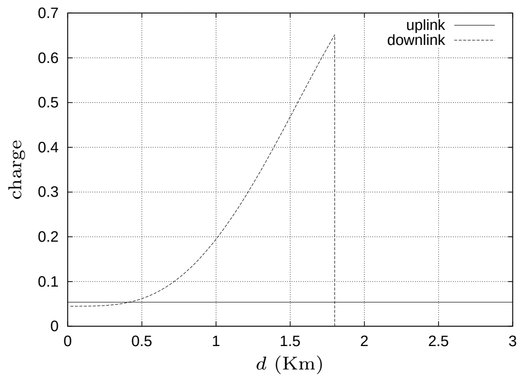
Next we present a brief overview of related work; this is not an exhaustive survey of the area, and has the goal to identify the main differences between other research and the work presented in this paper.

The authors of [4] consider a utility that is different from the utility that we consider, and is interpreted as the number of information bits transmitted per unit of energy. It is shown that the non-cooperative game, where mobiles adjust their power to maximize their utility, has a unique Nash equilibrium, which however is inefficient. With the introduction of prices [17], Pareto improvements are achieved, but not the social welfare optimal. On the other hand, the resource control model we have presented for the uplink, under some assumptions regarding the utility functions, achieves the social welfare maximum.

The authors of [20] consider a utility that is a function of the transmission rate, and investigate the problem of maximizing the sum of all utilities in the forward link (downlink), under constraints on the total transmission power at the

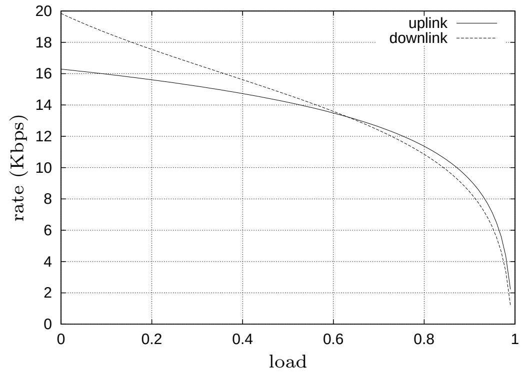


(a) Concave utility

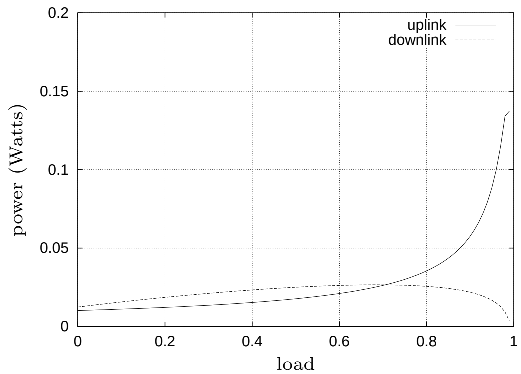


(b) Sigmoid utility

Figure 5: In the uplink, the charge is independent of the distance. In the downlink, the charge follows a shape similar to the power, Figure 4, since it is proportional to the power.



(a) Rate



(b) Power

Figure 6: The rate depends on the load more for the downlink than for the uplink. The power in the downlink initially increases, and then decreases. The mobile distance from the base station is $d = 0.5$ Km.

base station, and constraints on the maximum error rate for each user. The allocation of rates is done centrally at the base station. The approach proposed in Section 3.3, and given by (19), considers a similar objective, but with the utility being a function of the actual throughput (transmission rate multiplied by the success probability), rather than the transmitted rate. Moreover, our approach uses a decentralized scheme, based on prices, to achieve the objective.

The authors of [21] consider a utility that is a function of the bit-energy-to-noise-density ratio, which can have a sigmoid shape, and formulate a utility-based distributed power control algorithm where each user seeks the maximize his net utility, and charges are proportional to the power. For a constant price per unit of power, it is proved that the power update algorithm converges. The authors of [10] consider downlink resource allocation in CDMA networks based on pricing. The user utility is a step function of the bit-energy-to-noise-density ratio, and a mobile's charge contains a constant term (price per code) and a term linear in the transmitted power from the base station. The authors of [7] consider a utility that is a monotonically increasing concave function of the bit-energy-to-noise-density ratio and a monotonically decreasing concave function of the mobile's power.

Our work differs from the above in that it considers the joint optimization of the signal quality and transmission rate, and takes into account the particular resource constraints in both the downlink and uplink, identifying the differences of the two corresponding models; also, our framework takes into account the congestion for both wireless and wired network resources, in addition to the cost of mobile battery power. Moreover, the above approaches are geared towards mechanisms for power control; on the other hand, our work deals with control mechanisms that operate on a slower timescale, hence on top of fast closed-loop power control. Finally, in the model we have proposed for the uplink, there is no differentiation of mobile users based on their position. On the other hand, in the approaches of [4, 17, 21], mobile users far from the base station that encounter high path loss are charged more and receive less resources, compared to users close to the base station; this is termed 'near-far unfairness' in [21]. Investigation of the above schemes, and comparison with a resource control scheme based on microeconomics, similar to the one presented in this paper, but for traffic with fixed-rate requirements, appears in [19].

The concept of utility in wireless local area networks is considered in [1, 12]. In particular, the work of [1] uses utility curves for modelling application requirements, and based on this, for building adaptive QoS support in the MAC layer. The work of [12] uses the utility concept for defining fair contention resolution algorithms, taking into account unique characteristics of ad hoc wireless networks, such as location-dependent contention and decentralized control.

7. CONCLUDING REMARKS

We have presented a framework, based on microeconomics and congestion pricing, for resource control in CDMA, and Wideband CDMA in particular, networks carrying elastic traffic. An important property of the framework is that it incorporates the congestion for shared resources in both wireless and wired networks, as well as the cost of power consumption. Hence, it can be used as the basis for integration of control mechanisms in wireless and wired networks.

We have identified a number of practical issues regarding the application of the framework, and have presented a series of numerical investigations identifying its key features, and how various parameters such as a mobile's position and the wireless network's load, influence resource sharing.

Regarding the application of the proposed framework, different aspects of the framework have a different complexity. For example, currently the selection of the frame error rate for non-real-time services is fixed, equal to some (arbitrary) value in the range 10-20% [6, p. 198]. Typical outer loop power control procedures increase or decrease the target bit-energy-to-noise-density ratio in order to achieve this fixed frame error rate. On the other hand, we have seen that in order to achieve efficiency, the optimal target bit-energy-to-noise-density ratio should depend on the packet success probability as a function of the bit-energy-to-noise-density ratio, and in particular for best-effort traffic should satisfy (11). Moreover, as discussed in Section 4.1, the procedure for selecting the optimal bit-energy-to-noise-density ratio can take advantage of the sigmoid shape of the packet success probability, hence can be implemented with small modifications to the typical procedures used for outer loop power control. Also, the allocation of rates by the radio network controller (RNC) according to the willingness-to-pay values declared by all mobile users can be implemented as part of the load control functionality of the RNC, in a class-based framework where a different class corresponds to a different willingness-to-pay value. Based on the above discussion, the willingness-to-pay approach appears to require fewer modifications to existing procedures compared to the explicit price communication approach, since the latter places more intelligence in the mobile hosts; on the other hand, the explicit price communication approach places more control, hence flexibility, in the mobile hosts, and can be the basis for supporting the integration of congestion control in wireless and wired networks.

Issues we are currently investigating include the extension of the proposed framework for bursty traffic, for which a hybrid code and time division multiplexing scheme might be more appropriate [6], and for loss sensitive traffic, whose utility depends on the packet loss rate in addition to the average throughput. Another issue of practical nature is the fact that we have assumed that rates obtain continuous values, whereas rates in WCDMA can obtain discrete values, with the use of discrete spreading factors.

In this paper we introduced the idea of using ECN as the common signalling mechanism for conveying congestion information in wireless and wired networks, in order to support seamless congestion control over both network technologies. An area for further investigation is the necessary mechanisms to support the above. In particular, an important issue is that there is no shared buffer in the uplink direction, hence queue-based marking schemes such as Random Early Detection (RED) cannot be applied. Finally, we are investigating the application of microeconomic models for wireless network dimensioning, and for resource control in wireless LANs based on IEEE 802.11.

The overall goal of the above work is to further the research on the application of microeconomic models for developing efficient, flexible, and robust mechanisms for resource control in wireless networks; this includes both modelling work that takes into account the particular characteristics of wireless networks, and more practical engineering investigations on how to modify and enhance existing mechanisms in order to implement these models.

8. ACKNOWLEDGMENTS

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