Congestion Sensitive Downlink Power Control for Wideband CDMA Systems

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***Abstract*— We present a model for efficient and robust power control in the downlink of Wideband CDMA wireless systems. The model is based on microeconomics, and takes into account both the congestion, in terms of increased interference, that a mobile user imposes to other users, and the downlink resource constraint, which involves the total transmission power at the base station. We discuss the application of the model for supporting service differentiation, and investigate various alternatives and their corresponding tradeoffs. Our approach involves adjusting the target signal quality based on weights declared by mobile users.**

Keywords: power control, congestion pricing, social welfare, service differentiation

I. Introduction

Current power control algorithms for wireless systems increase the power when the interference increases, in order to satisfy the requested signal qualities. However, when the requested signal qualities are infeasible, the above power control algorithms diverge. Such behavior results from not taking into account the fact that wireless resources are limited, and that the increase of the power of one mobile user imposes a congestion cost, in terms of increased interference, to the other users.

In this paper we present a model that takes into account the above congestion costs, hence enables efficient utilization of wireless resources (transmission power at the base station), and is robust to the demand for such resources. Our model is based on microeconomics and congestion pricing, and considers utility functions for expressing user preferences. We discuss the application of our model for supporting service differentiation in wireless networks. Our approach involves modifying the outer loop power control algorithm, which adjusts the target signal quality, expressed by the bit-energy-to-noise-density ratio[1], based on weights declared by the mobile users. Hence, the approach does not require changes to fast closed-loop power control, whose objective is to adjust the transmission power in order to achieve the target signal quality. In this paper we consider the case of traffic with fixed rate requirements, which can adjust their signal quality. Resource control, for both the uplink and the downlink, in the case of traffic which is adaptive to both the transmission rate and signal quality is investigated in [11].

The application of microeconomic models to power control has also been proposed by other researchers, e.g., see [12], [3], [9], [7], [6], [1]. The authors of [12] consider a scheme, called utility-based power control, where the user optimization problem is the same as the one considered in this paper. The work of [3], [9] also assume the same user problem, but consider a different utility that can be interpreted as the number of information bits transmitted per unit of energy, and is not an increasing function of the transmission power. A main difference between our work and the above is that we investigate the problem of power control in the context of social welfare maximization, taking into account the total transmission power constraint at the base station. As a result, our model yields economically efficient power allocations. Moreover, the application of our model involves adjusting the target signal qualities, based on the declared weights of all mobile users, hence works on top of the fast closed-loop power control procedure defined for Wideband CDMA systems.

Downlink power control is also discussed in [7], but the interference a mobile user causes to the others is not taken into account. Finally, uplink power control control is investigated in [6], [1].

The rest of this paper is organized as follows. In Section II we discuss resource usage in the downlink of CDMA systems, and based on this we present our model for resource control using the notions of utility functions and congestion pricing. In Section III we discuss the application of our model for supporting service differentiation, and in Section IV we present numerical investigations using the proposed procedures. Finally, Section V concludes the paper identifying related issues we are currently investigating.

II. Model

In this section we first discuss resource usage in the downlink of WCDMA systems, and then present our model for resource control based on utility functions and congestion pricing.

[1]The bit-energy-to-noise-density ratio is also referred to as signal-to-interference ratio (SIR).

A. Resource usage in the CDMA downlink

The value of the bit-energy-to-noise-density ratio E_b/N_0 corresponds to the signal quality, since it determines the bit error rate, *BER* [2], [13]. Indeed, *BER* is a non-decreasing function of E_b/N_0, that depends on the multipath characteristics, and the modulation and forward error correction (FEC) algorithms. Let γ be the target bit-energy-to-noise-density ratio required to achieve a target *BER*. The target bit-energy-to-noise-density ratio is selected by *outer loop power control* in WCDMA systems, and is given to *closed-loop power control*, which adjusts the transmission power in order to achieve this target. If we assume perfect power control, then for user i we have $(E_b/N_0)_i = \gamma_i$, which in the case of a single cell is given by [2], [13]

$$\gamma_i = \frac{W}{r_i} \frac{g_i p_i}{\theta_i g_i \sum_{k \neq i} p_k + \eta_i} , \quad (1)$$

where W is the chip rate, 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, θ_i is the orthogonality factor for the codes used in the downlink, and η_i is the power of the background noise at mobile i. From (1), observe that a mobile user's signal quality is affected by the transmission power of the signals to all users, i.e., $\gamma_i = \gamma_i(p_1, \ldots, p_N)$.

In the downlink, the total power with which a base station can transmit is limited, hence

$$\sum_{i=1}^{N} p_i \leq P ,$$

where N is the number of mobiles and P is the total transmission power from the base station. From the last equation, observe that the amount of resources used by each mobile is given by the corresponding transmission power of the signal destined to that mobile. Unlike the downlink, which is *power-limited* and resource usage is determined from the transmission power, the uplink is *interference-limited* and resource usage is determined from the product $r_i \gamma_i$ [8], [13].

B. Resource control in the CDMA downlink

Next we present a model for resource control, based on the notions of utility and congestion pricing. We consider rate-inelastic traffic, i.e., traffic which has fixed rate requirements, but can adapt its target bit-energy-to-noise-density ratio. Such applications include, e.g., streaming video/audio, which can have a fixed transmission rate, but whose quality, as perceived by users, depends on the frame error rate; the latter depends on the signal quality, which as discussed above is determined by the target bit-energy-to-noise-density ratio.

The utility for a user i with rate-inelastic traffic can be expressed by $U_i(\gamma_i(p_1, \ldots, p_N))$. Consider the problem of allocating transmission powers p_i, for $i = 1, \ldots, N$, in order to maximize the social welfare

$$\max_{\{p_1, \ldots, p_N\}} \sum_{i=1}^{N} U_i(\gamma_i(p_1, \ldots, p_N)) , \quad \text{subject to} \quad \sum_{i=1}^{N} p_i \leq P . \quad (2)$$

The Lagrangian for (2) is given by

$$L = \sum_i U_i(\gamma_i(p_1, \ldots, p_N)) + \mu(P - \sum_i p_i) ,$$

where μ is the shadow price for the constraint on the total transmission power at the base station. The first order conditions for the above Lagrangian are

$$\frac{dU_i(\gamma_i)}{dp_i} + \sum_{j \neq i} \frac{dU_j(\gamma_j)}{dp_i} - \mu = 0 \quad \text{for} \quad i = 1, \ldots N ,$$

Substituting (1) in the last equation we obtain

$$U_i'(\gamma_i) \frac{W}{r_i} \frac{g_i}{\theta_i g_i \sum_{k \neq i} p_k + \eta_i} - \sum_{j \neq i} \left[U_j'(\gamma_j) \frac{W g_j p_j}{r_j} \frac{\theta_j g_j}{(\theta_j g_j \sum_{k \neq j} p_k + \eta_j)^2} \right] - \mu = 0 .$$

When there is a large number of mobiles, the last equation can be approximated by

$$U_i'(\gamma_i) \frac{W}{r_i} \frac{g_i}{\theta_i g_i \sum_k p_k + \eta_i} - \sum_j \left[U_j'(\gamma_j) \frac{W g_j p_j}{r_j} \frac{\theta_j g_j}{(\theta_j g_j \sum_k p_k + \eta_j)^2} \right] - \mu = 0 . \quad (3)$$

In the last equation, the second term represents the marginal congestion cost, in terms of interference, that user i imposes to all other users, and the third term μ represents the shadow price for the constraint on the total transmission power at the base station. Indeed, by having users face the price λ given by

$$\lambda = \sum_j \left[U_j'(\gamma_j) \frac{W g_j p_j}{r_j} \frac{\theta_j g_j}{(\theta_j g_j \sum_k p_k + \eta_j)^2} \right] + \mu ,$$

then a user i's objective of maximizing his benefit (utility minus charge),

$$\max_{p_i} U_i(\gamma_i) - \lambda p_i ,$$

has the same first order condition as (3), i.e., the individual user optimization coincides with the global social welfare optimization; a pricing scheme with this property is called *incentive compatible*. Indeed, it is interesting to note that the user does not differentiate the two factors in (3), i.e., the marginal congestion cost and the shadow price for the power contraint, and sees only the sum of these two factors.

Next we consider the special case where the user utilities are logarithmic functions. Such a case provides insight to the above results, and will be the basis of the simple approach that we present in the next section for applying our model in order to achieve service differentiation.

Consider the utility $U_i(\gamma_i) = w_i \log \gamma_i$. Substituting this utility in (3) we obtain

$$\frac{w_i}{p_i} - \sum_j w_j \frac{\theta_j g_j}{\theta_j g_j \sum_k p_k + \eta_j} - \mu = 0 \,.$$

From the last equation observe that, for logarithmic utilities, the power p_i is proportional to the weight w_i; hence the latter represents a willingness-to-pay for user i, which can be interpreted as the (constant) charge per time unit that the user is willing to pay for obtaining wireless resources, which for the downlink is given by the transmission power. Indeed, such a model can be the basis for a fair and incentive compatible pricing scheme, since charges would be proportional to resource usage.

Due to the proportional dependence of the power on the weight (willingness-to-pay) factor, the optimal allocation of powers is given by

$$p_i = \frac{w_i}{\sum_j w_j} P \quad \text{for} \quad i = 1, \ldots, N \,. \tag{4}$$

The above allocation of powers satisfies the first order conditions (3) and the power constraint in (2). Moreover, observe that the last equation can form the basis for robust power control, since a higher demand results in a larger sum of weights, hence a smaller allocation of power to individual mobiles. We investigate the application of the last equation for service differentiation in the next section.

III. Application of the model

Due to multipath fading, the selection of the instantaneous transmission power based on (4) has the disadvantage that the received signal quality at a mobile host will not be constant. Moreover, it requires modification of the fast closed-loop power control procedure, which is implemented in the physical layer of CDMA systems.

Another alternative involves estimating a signal quality, which is then used as the target in fast closed-loop power control. Let $\bar{p}_i$ be the average power for user i. Due to factors such as fast fading, shadowing, inter-cell interference, and imperfect power control, the target power utilization ρ will be lower than one, and it can show that, similar to (4), the average power is

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

From (1), and assuming that the base station achieves the maximum power utilization, the target signal quality for user i will be

$$\gamma_i = \frac{W}{r_i} \frac{1}{\bar{l}_i \bar{I}_i} \frac{w_i}{\sum_j w_j} \rho P \,, \tag{5}$$

where $\bar{I}_i$ is the average interference and $\bar{l}_i$ is the average loss for user i, where $l_i = 1/g_i$. From the last equation observe that, as was the case for the power, the signal quality is proportional to the weight factor.

Equation (5) requires estimation of the channel gain from the base station to the mobile, which can be done using the downlink pilot bits. There are two options as to where the selection of γ_i based on (5) is performed: the mobile host or the radio network controller (RNC). The first alternative results in more complexity at mobile hosts. Moreover, it requires communicating the ratio $\rho P / \sum_j w_j$ from the RNC to the mobile. On the other hand, if the RNC performed the selection of γ_i, then there would be increased signalling overhead since the mobile would need to communicate to the RNC the values of the gain and interference; such communication would be required whenever these parameters changed, e.g., due to mobility. We note that, in order to avoid signalling overhead and delays, the selection of the target bit-energy-to-noise-density ratio in WCDMA is performed at the mobile [5, p. 197].

From (5) observe that, for the same weight, a smaller path gain will result in a smaller signal quality, i.e., a worst quality of service. Hence, mobile users at a different distance from the base station receive different service. However, note that $I_i = \theta_i g_i \sum_{k \neq i} p_k + \eta_i \approx \theta_i g_i \rho P + \eta_i$, in the case of a large number of mobiles. Hence, when the noise is negligible, then the distance does not affect the signal quality.

A second alternative that avoids the above differentiation due to a mobile's position, is to use (5) after replacing the parameters with their corresponding averages *over all mobile hosts*. Hence, if $\bar{I}$ is the average interference and $\bar{l}$ is the average loss over all mobiles, then the allocation of signal qualities can use the following equation

$$\gamma_i = \frac{W}{r_i} \frac{1}{\bar{l} \bar{I}} \frac{w_i}{\sum_j w_j} \rho P \,. \tag{6}$$

If implemented at the RNC, the last equation requires estimation and communication of the average interference from the mobile to the RNC. An alternative which does not require communication of parameters other than the target γ_i is to adaptively adjust a parameter ν, which corresponds to a dynamic price, based on

$$\frac{d\nu}{dt} = \kappa(\bar{p} - \rho P) \,, \tag{7}$$

where $\bar{p}$ is the average total transmission power from the base station, ρ is a target power utilization, and κ determines the speed of convergence of the system. The signal quality for user i would be

$$\gamma_i = \frac{w_i}{r_i \nu} \,. \tag{8}$$

Note that, according to the above model, the price ν remains internal to the RNC and is not communicated to the mobile hosts. Another option is to communicate the congestion price to the mobile hosts, which are free to adjust their signal quality according to their needs and requirements.

The procedures of this section assumed logarithmic user utilities. They can be extended for more general forms of the user utility $U_i(\gamma_i)$, by assuming that a user smoothly adjusts his weight according to

$$w_i(t) = U_i'(\gamma_i(t-1))\gamma_i(t-1)\,, \tag{9}$$

where $\gamma_i(t-1)$ is the signal quality allocated to user i at the time interval $t-1$.

As already noted, the above procedures involve modification of outer loop power control, which operates on much slower timescales than fast closed-loop power control. Moreover, a mobile user's weight can be determined at his subscription phase, during connection setup, or renegotiated during a connection. Such an approach is similar to the class-based quality of service framework presented in [4].

IV. Numerical investigations

Next we present numerical investigations that demonstrate the properties and differences among the resource sharing procedures presented in the previous section. The values of the parameters considered in the experiments are shown in Table I.

First assume that all mobile users have a logarithmic utility, with the same weight factor. The target signal quality γ as a function of the distance is shown in Fig. 1. As expected, when resource allocation is based on Eq. (5), where there is no averaging over all mobiles, the target signal quality γ decreases with the distance, since the congestion charge is proportional to the transmission power, and the required power to achieve a given signal quality increases with the distance. On the other hand, when resource allocation is based on Eq. (6), there is no differentiation due to a mobile's position, since now a mobile's charge does not depend solely on its own transmission power but on the average transmission power to all mobiles. In Fig. 1 we have assumed that the average loss and the average interference over all mobiles corresponds to the loss and interference for a mobile whose distance from the base station is 1 Km.

Note that, in the equilibrium, resource allocation based on Eq. (5) is the same as resource allocation based on the dynamic pricing scheme in Eq. (8), when the target power utilization in Eq. (5) is the same as that in Eq. (7). The two schemes differ in

TABLE I

PARAMETERS FOR THE NUMERICAL INVESTIGATIONS. d IS DISTANCE IN KM.

parameter	value
chip rate, W	3.84 Mcps
noise, η	10^{-13} Watt
total BS power, P	10 Watt
load	50%
path gain, $g(d)$	kd^{-u}, $u = 3.52$, $k = 1.82 \cdot 10^{-14}$
downlink orthogonality, θ	0.1
rate, r	30 Kbps
# of sources, N	25

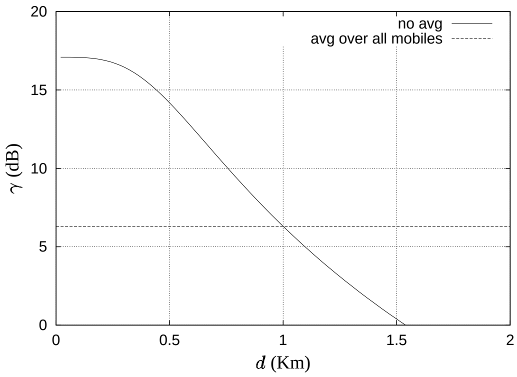

Fig. 1. When there is no averaging over all mobiles, Eq. (5), a mobile farther from the base station achieves a smaller γ. Such differentiation can be avoided if the path loss and interference is averaged over all mobiles, Eq. (6).

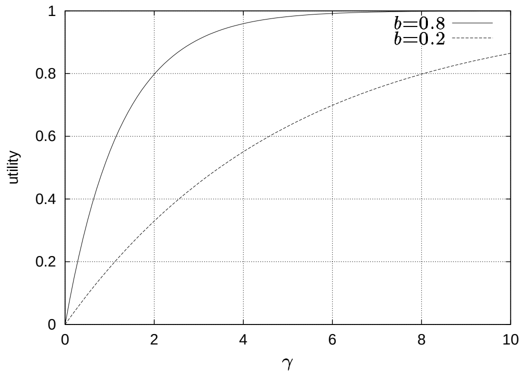

Fig. 2. Utility $U(\gamma) = 1 - e^{-b\gamma}$, for $b = 0.8$ and $b = 0.2$.

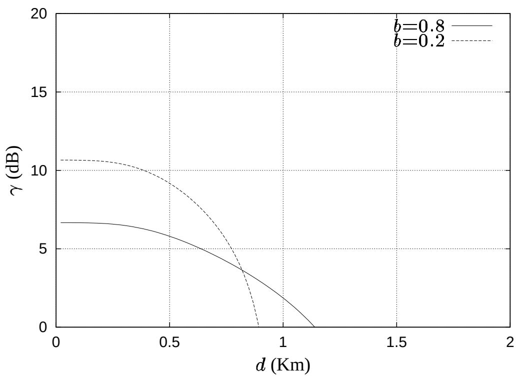

Fig. 3. For small distances, γ is higher for the less steep utility ($b = 0.2$), compared to the steeper utility ($b = 0.8$). Moreover, γ drops to zero at a smaller distance for the less steep utility.

that the time to reach the equilibrium with the dynamic pricing scheme is larger, and depends on the parameter κ in Eq. (7). On the other hand, as discussed in the previous section, the dynamic pricing scheme involves less communication overhead.

Now assume that one of the N $(= 25)$ mobile users has a utility function of the form $U(\gamma) = 1 - e^{-b\gamma}$, Fig. 2. Figure 3 shows the signal quality as a function of distance for the two utilities shown in Fig. 2, when resource allocation is based on Eq. (5) and (9). From this figure we observe that the less steep utility ($b = 0.2$ in Fig. 2) achieves for small distances a higher target signal quality γ. This can be explained by considering the derivative of the utility in Fig. 2 and Eq. (5) and (9). In particular, the same derivative $U'(\gamma)$ in Fig. 2 is achieved at a higher γ for the less steep utility ($b = 0.2$), compared to the steeper utility ($b = 0.8$).

Also observe in Fig. 3 that at some distance, γ drops to zero. Indeed, the distance at which this occurs is smaller for the less steep utility ($b = 0.2$), compared to the steeper utility ($b = 0.8$). This observation can be explained by the fact that $U'(\gamma)$ obtains larger values for the steeper utility. This observation together with Eq. (5) and (9) shows that, for the steeper utility, γ obtains non-zero values for larger distances.

V. Conclusions

We have presented a model, based on microeconomics and congestion pricing, for efficient and robust power control in the downlink of CDMA wireless systems. We have discussed the application of the model for supporting service differentiation, investigating various alternatives and their corresponding trade-offs. We have considered traffic with fixed rate requirements, which can adjust their signal quality. The case of traffic which can adjust both their transmission rate and signal quality is considered in [11].

The work presented in this paper is part of a wider effort whose goal is to investigate the application of ideas from microeconomic modelling for developing flexible, efficient, and robust procedures for resource control in wireless networks. In this direction, issues we are investigating include resource and cell dimensioning [10], integration of congestion control mechanisms in wireless and wired networks, and resource control and service differentiation in Wireless LANs based on 802.11.

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References

[1] T. Alpcan, T. Basar, R. Srikant, and E. Altman. CDMA uplink power control as a non-cooperative game. In *Proc. of IEEE Conf. On Decision and Control*, December 2001.

[2] K. S. Gilhousen and *et al*. On the capacity of a cellular CDMA system. *IEEE Trans. on Vehicular Technology*, 40(2):303–312, May 1991.

[3] D. J. Goodman and N. B. Mandayam. Power control for wireless data. *IEEE Personal Commun.*, 7:48–54, April 2000.

[4] Y. Guo and H. Chaskar. Class-based quality of service over air interfaces in 4G mobile networks. *IEEE Commun. Mag.*, pages 132–137, March 2002.

[5] H. Holma and A. Toskala. *WCDMA for UMTS (revised edition)*. Wiley, New York, 2001.

[6] H. Ji and C.-Y. Huang. Non-cooperative uplink power control in cellular radio systems. *ACM/Baltzer Wireless Networks Journal*, 4:233–240, 1998.

[7] P. Marbach and R. Berry. Downlink resource allocation and pricing for wireless networks. In *Proc. of IEEE INFOCOM'02*, 2002.

[8] A. Sampath, P. S. Kumar, and J. M. Holtzman. Power control and resource management for a multimedia CDMA wireless system. In *Proc. of IEEE Int. Symp. Personal, Indoor, Mobile Radio Commun. (PIMRC)*, Toronto, Canada, 1995.

[9] C. U. Saraydar, N. B. Mandayam, and D. J. Goodman. Efficient power control via pricing in wireless data networks. *IEEE Trans. Commun.*, 50(2):291–303, February 2002.

[10] V. A. Siris. Cell coverage based on social welfare maximization. In *Proc. of IST Mobile and Wireless Telecommunications Summit*, June 2002.

[11] V. A. Siris. Resource control for elastic traffic in CDMA networks. In *Proc. of ACM International Conference on Mobile Computing and Networking (MOBICOM)*, September 2002.

[12] M. Xiao, N. B. Shroff, and E. K. P. Chong. Utility-based power control in cellular wireless systems. In *Proc. of IEEE INFOCOM'01*, 2001.

[13] L. C. Yun and D. G. Messerschmitt. Power control for variable QoS on a CDMA channel. In *Proc. of IEEE MILCOM'94*, NJ, USA, 1994.