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ECONOMIC MODELS FOR RESOURCE CONTROL IN WIRELESS NETWORKS

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Abstract - We present a model based on congestion pricing for resource control in wireless CDMA networks carrying traffic streams that have fixed-rate requirements, but can adapt their signal quality. Our model considers the resource usage constraint in the uplink of CDMA networks, and does not differentiate users based on their distance from the base station. We compare our model with other economic models that have appeared in the literature, identifying their similarities and differences. Our investigations include the effects of a mobile's distance and the wireless network's load on the target signal quality, the transmission power, and the user benefit.

Keywords - resource usage, utility, congestion pricing, signal quality adaptation

I. INTRODUCTION

The widespread use and limited capacity of mobile wireless networks is making the efficient utilization and control of limited resources in such networks increasingly important. In addition to simplicity and efficient implementation, procedures for resource control should have a theoretically sound underlying model, which induces the efficient use of resources based on the actual requirements of mobile users. The goal of this paper is to propose and investigate such a model, which is based on economic modelling, and compare it with other models that have appeared in the literature.

Economic models, based on the notions of utility functions and congestion pricing, have been successfully applied to fixed wired networks, e.g., see [5], [6], [1]. Economic models have also been proposed for wireless networks, e.g., see [3], [8], [10]. Such models can guide the development of flexible and robust procedures for efficient utilization of network resources, based on actually user requirements and preferences. Common features of the above models is that a user's requirements are expressed in the form of a utility function, which gives the level of user satisfaction for a given level of service, and "prices" are used as a control mechanism to affect user behavior. Note that although economic models use the notion of prices, these can be seen solely as an internal control mechanism, and need not reflect the actual charges that end-users pay.

We consider CDMA wireless networks carrying traffic streams with fixed-rate requirements, that can adjust their signal quality, the latter determined by the bit-energy-to-noise-density ratio at the receiver. Examples include streaming applications with fixed-rate requirements, that can adapt their picture quality, which is determined by the percentage of lost data over the wireless channel. Our model considers the resource usage constraint in the uplink of CDMA networks, and has the important property that it does not differentiate users based on their distance from the base station. Moreover, resource allocation based on our model depends on the load of the wireless network, which can be estimated from aggregate measurements of the interference.

Although our model is presented in the context of CDMA networks, it can potentially be applied to other wireless technologies, where a single transmission produces interference to other transmissions; such is the case of multiple WLANs in geographic proximity. Moreover, we are currently investigating the application of economic models to other problems in wireless networks, such as determining the cell coverage, power control, and service differentiation.

The rest of this paper is organized as follows. In Section II we discuss resource usage in the uplink direction of CDMA, and propose a model for resource control based on congestion pricing. In Section III we discuss two models based on economics that have been proposed in the literature, and in Section IV we present numerical investigations comparing these models with the one proposed in Section II. Finally, Section V concludes the paper.

II. RESOURCE CONTROL BASED ON CONGESTION PRICING

In this section we first discuss resource usage in CDMA networks. Then, based on the results for resource usage, we propose a model for resource control based on congestion pricing, in the case of fixed-rate traffic streams that can adjust their signal quality.

Consider the uplink of a single CDMA cell. Let W be the chip rate. The bit-energy-to-noise-density ratio at the base station is given by [2], [11]

$$\left(\frac{E_b}{N_0}\right)_i = \frac{W}{r_i}\frac{g_i p_i}{\sum_{j\neq i} g_j p_j + \eta}\,, \tag{1}$$

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, and η is the power of the background noise at the base station. The ratio W/r_i is the spreading factor or processing gain for mobile 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* [2], [11]. Under the realistic assumption of additive white Gaussian noise, *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_i be the target bit-energy-to-noise-density ratio required to achieve a target *BER*. This target is given to closed-loop power control, which adjusts the transmission power in order to achieve it.

If we assume perfect power control, in which case $(E_b/N_0)_i = \gamma_i$, and solve the set of equations given by (1) for each mobile i, we get [11], [7]

$$g_i p_i = \frac{\eta \alpha_i^{\text{UL}}}{1 - \sum_j \alpha_j^{\text{UL}}} \,, \tag{2}$$

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

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

The power levels given by the set of equations (2) 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 (2) we get

$$\sum_i \alpha_i^{\text{UL}} < 1 \,. \tag{3}$$

The last equation illustrates that the uplink is *interference-limited*: Even when they have no power constraints, mobiles cannot increase their power with no bound, due to the increased interference they would cause to the other mobiles. If (3) is violated, then the target $\{\gamma_i\}$ cannot be met for all mobiles.

When there is a large number of mobile users, each using a small portion of the available resources, we have $\frac{W}{r_i \gamma_i} \gg 1$, hence $\alpha_i^{\text{UL}} \approx \frac{r_i \gamma_i}{W}$ and the resource constraint (3) can be approximated by

$$\sum_i r_i \gamma_i < W \,. \tag{4}$$

The above analysis can be extended to take into account cases where there are constraints on the maximum power a mobile can transmit, and to take into account the interference from neighboring cells and imperfect power control. These extensions involve multiplying the right-hand side of equations (3) and (4) with a factor that is smaller than 1.

Next we discuss a model for resource control, based on the notions of utility and congestion pricing. We consider rate-inelastic 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 is expressed by the target bit-energy-to-noise-density ratio. A possible expression for the utility of rate-inelastic traffic is

$$U_{in}(r, \gamma) = U_r(r) U_q(\gamma) \,,$$

where $U_r(r)$, due to the inelasticity in terms of the rate, is a step function, and $U_q(\gamma)$ can be an increasing concave or a sigmoid function. A utility with a sigmoid shape is able to capture minimum requirements in terms of γ.

Recall that in the case of a large number of mobile hosts, the wireless resource constraint is given by (4). In order to provide the right incentives for efficient use of network resources, user i should face a congestion charge that is proportion to his resource usage, which based on (4) is given by the product $r_i \gamma_i$. Facing such a charge, a user will seek to maximize his benefit (net utility), hence performs the following optimization (without loss of generality, we assume that $U_r(r_{min}) = 1$):

$$\max_{\gamma_i \geq 0} U_{q,i}(\gamma_i) - \lambda r_{min,i} \gamma_i \,, \tag{5}$$

where λ is the shadow price for wireless resources in the uplink direction. If the net utility objective function in (5) is negative for all values of the signal quality γ_i, then the net utility is maximized, and equals zero, if $r_i = 0$, i.e., the corresponding user does not use the wireless network.

The optimal γ_i^* for achieving the maximum in (5) satisfies

$$U'_{q,i}(\gamma_i^*) = \lambda r_{min,i} \,.$$

If $U_{q,i}(\gamma_i)$ is an increasing and strictly concave function of γ_i, then an optimal γ_i^* exists and is unique. Moreover, under the above assumptions on the utility, one can prove that there exists a shadow price λ such that the resulting allocations from the above net utility maximization also maximize the aggregate utility (social welfare) of the system [9]. Hence, the optimal allocation of resources can be achieved in a decentralized and distributed fashion by having the base station communicate the price λ to all mobiles, which react by adjusting their signal quality based on (5).

The shadow price λ should be an increasing function of the network load. One such function, which we will consider in our numerical investigations, is the following

$$\lambda = \frac{a_{cp}}{1 - \rho} \,,$$

where $\rho = \sum_i \alpha_i$ is the total load. Note that the latter can be estimated from measurements of the total interference I_{total} (which includes the noise), and the noise power η using [4]

$$\sum_i \alpha_i = \frac{I_{total} - \eta}{I_{total}} \,. \tag{6}$$

The above model has assumed traffic streams with fixed-rate requirements, that can adapt their signal quality. Investigation of models for the case of elastic (best-effort) traffic streams, that value only their average data throughput, and can vary both the signal quality and the transmission rate is contained in [9].

III. ECONOMIC MODELS FOR RESOURCE CONTROL

In this section we discuss two economic models that have been proposed for resource control in wireless networks: non-cooperative power control game with pricing [3], [8], and utility-based power control [10]. Note that our objective and focus is to compare these models with the one based on congestion pricing presented in the previous section. The mechanisms built from the models can differ. For example, both the models in [3], [8] and [10] are targeted at developing procedures for closed-loop power control. One the other hand, our model based on congestion pricing is geared to selecting the signal quality that maximizes a user's benefit; this selection of signal quality is the role of open-loop power control. The optimal signal quality selected through open-loop power control is given to closed-loop power control, which adjusts a mobile's transmission power to achieve it.

A. Non-cooperative power control game with pricing (NPGP)

The authors of [3], [8] propose a procedure for power control, using the notions of utilities and pricing. The utility function considered has the form

$$\frac{L r_i P_s(\gamma)}{M p_i}$$

where L is the number of information bits transmitted in packets of length M. The above utility can be interpreted as the number of information bits transmitted per unit of energy, and has the property that it initially increases with increasing power, equivalently with increasing bit-energy-to-noise-density ratio, but after some value decreases with increasing power.

To increase the efficiency of power allocations, the authors introduce prices that are proportional to the power. According to the scheme, called non-cooperative power control game with pricing (NPGP), each mobile user i adjusts his transmission power p_i, or equivalently his target bit-energy-to-interference-density ratio γ_i, to achieve the following optimization (for simplicity we assume that $L = M$):

$$\max_{\gamma_i \geq 0} \frac{r_i P_s(\gamma_i)}{p_i} - \lambda_{npgp} p_i \,, \tag{7}$$

where $P_s(\gamma_i)$ is the packet success rate. The price per unit of power λ_{npgp} is independent of the load in the wireless network. In [3], [8], a function slightly different from the packet success rate is used; this is done to avoid the degenerate case where the first term in (7) becomes infinite, since $P_s(0) > 0$, i.e., the percentage of successful bits is greater than zero, even when γ, hence the power p, are zero.

B. Utility-based power control (UBPC)

The authors of [10] also investigate the problem of distributed power control. They propose a procedure, called utility-based power control (UBPC), for power control in the downlink direction; here we consider its application to the uplink. According to the approach, each mobile adjusts its transmission power p, equivalently the target bit-energy-to-interference-density ratio γ, to achieve the following maximization:

$$\max_{\gamma_i \geq 0} U_i(\gamma_i) - \lambda^i_{ubpc} p_i \,. \tag{8}$$

The authors prove, for fixed λ^i_{ubpc}, that a distributed power control algorithm based on the above model converges. The price per unit of power λ^i_{ubpc} can be taken to reflect the congestion experienced by a user, in which case the following formula is proposed

$$\lambda^i_{ubpc} = a_{ubpc}(I_i + \eta) \,,$$

where a_{ubpc} is a constant and I_i is the interference experienced by the signal from mobile i at the base station, due to the signals from the other mobiles. From the above, note that the price per unit of bandwidth can be different for different mobile users.

In our investigations we consider the case of a large number of mobiles, hence $I_i \approx I$, for all i, where I is the sum of the power of all signals received at the base station. If $\rho = \sum_i \alpha_i$ is the total load, then $I + \eta = I_{total}$ combined with (6) gives

$$I_i + \eta \approx I_{total} = \frac{\eta}{1-\rho} \,.$$

IV. NUMERICAL INVESTIGATIONS

The three schemes presented in the previous sections have different objectives. Hence, rather than comparing them in terms of aggregate measures such as the sum of utilities, we will compare them in terms of the target E_b/N_0, the utility, and the power in the steady state, and how these depend on the mobile's distance from the base station and the total load of the wireless network.

For the numerical comparisons, the price a_{cp} ($= 1.225$ Kbps^{-1}) was selected so that in the equilibrium the load is $\rho = 0.60$, when there are $N = 40$ mobiles, all with the same utility $U(\gamma) = 1 - e^{-0.8\gamma}$ and rate $r = 10$ Kbps; moreover, the constant a_{ubpc} ($= 1.023 \cdot 10^{13}$ Watt^{-2}) was selected so that at distance $d_0 = 0.5$ Km, the UBPC scheme gives the same target γ as the congestion pricing (CP) scheme. Finally, we set $\lambda_{npgp} = \frac{a_{ubpc}\eta}{1-\rho} = 2.558$ Watt^{-1}, for $\rho = 0.60$ and $\eta = 10^{-13}$ Watt. The price per unit of power in both the NPGP and the UBPC schemes, for load $\rho = 0.60$, is the same; note, however, that the price in the UBPC scheme depends on the load, whereas in the NPGP scheme it is independent.

The propagation model we consider is the Okumara-Hata model [4], which for an urban environment gives

$$L(d) = 137.4 + 35.2 \log_{10}(d) \,, \tag{9}$$

where $L(d)$ is the path loss in dB and d the distance from the base station in Km.

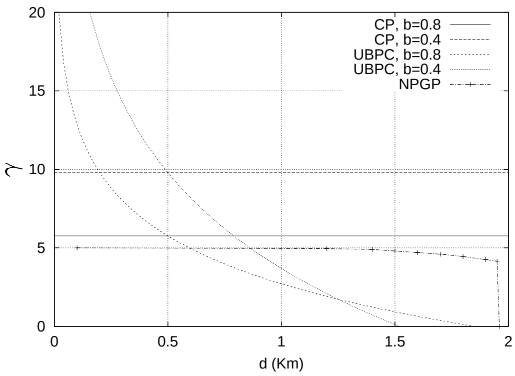

Fig. 1. For CP, γ is independent of the distance, since charges are independent of the distance. On the other hand, for UBPC, charges depend on the transmitted power, and γ decreases with the distance. For NPGP, γ decreases only slightly with the distance, and at some point falls abruptly to zero. (b is factor that appears in the exponent of the utility)

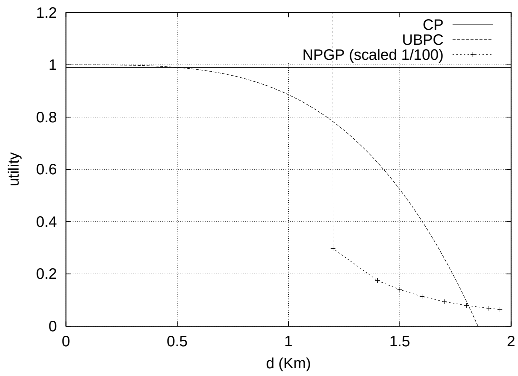

Fig. 2. For CP, the utility is independent of the distance, which is expected since γ is also independent of the distance. On the other hand, for UBPC, the utility is a concave function of the distance, whereas for NPGP the utility is a convex function of the distance.

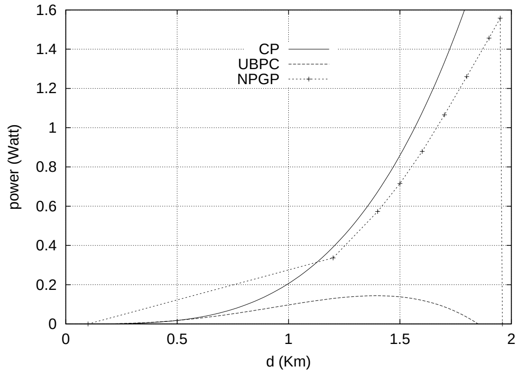

Fig. 3. The power for UBPC initially increases, but then starts to decrease; this is due to the combination of two effects: γ decreases with the distance, as shown in Fig. 1, but also the path loss increases.

Fig. 1 shows that for the congestion pricing (CP) scheme, the target bit-energy-to-noise-density ratio γ is independent of the mobile's distance from the base station, since the charge does not depend on the distance. On the other hand, for UBPC, charges depend on the transmitted power; as a result, γ decreases with the distance. Indeed, the dependence of signal quality with the distance is termed *near-far unfairness* in [10]. Finally, for the NPGP we find that the signal quality decreases only slightly with the distance, and at some distance falls abruptly to zero; at the distance where this sudden decrease occurs, sending even with a small power results in a negative net utility, hence it is preferable not to send at all.

Fig. 1 also shows that, for UBPC, with a less steep utility ($1 - e^{-0.4\gamma}$ is less steep compared to $1 - e^{-0.8\gamma}$), the dependence of γ with the distance is steeper. For CP, a less steep utility results in a larger value for γ.

Fig. 2 shows that the utility of a user in the CP approach is independent of the distance, which is expected since γ is also independent of the distance, Fig. 1. On the other hand, for UBPC, the utility is a decreasing and concave function of the distance. Finally, for NPGP the utility is a decreasing and convex function of the distance.

Fig. 3 shows that under the CP approach, a mobile's transmission power increases fast with the distance; this occurs because in order to achieve a constant γ, the power must increase with the distance to balance the increased path loss. With the UBPC approach, the power initially increases with the distance. This is due to the initial convex dependence of γ on the distance, Fig. 1. For example, assume $\gamma \propto r^{-1}$. From (1), with $(E_b/N_0)_i = \gamma_i$ and assuming that there is a large number of mobiles, we get (for simplicity, we have dropped the subscripts)

$$p \approx (I + \eta)\frac{r}{W}\frac{\gamma}{g}\,.$$

since $g \propto d^{-3.52}$, see (9), from the last equation we have that $p \propto d^{2.52}$; hence, for small distances, the power increases with the distance.

After some distance, the dependence of γ on the distance becomes approximately linear, Fig. 1, and as a result the power decreases with the distance. For example, if $\gamma \propto 1 - ad$ (where $a > 0$), then using the last equation we have that $p \propto d^{3.52} - ad^{4.52}$; hence, after some distance, the power decreases with the distance.

For NPGP, the power initially increases fast with the distance. The behavior of the power is similar in the CP scheme, only that the rate of increase in the CP scheme is slightly higher than in the NPGP scheme; this is because in the NPGP scheme γ decreases slightly with the distance. At some distance, for NPGP, the signal quality γ falls to zero, hence so does the power.

Up to now, we have assumed a fixed load. Next we investigate the behavior of the three algorithms when the network load changes.

Fig. 4 shows that γ depends more on the load for UBPC than for CP. Nevertheless, with UBPC the dependence of the signal quality on the load is higher compared to the depen-

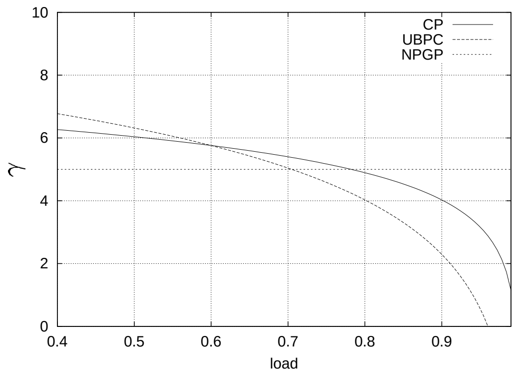

Fig. 4. For NPGP, γ is independent of the load, whereas for UBPC and CP it decreases with the load. Indeed, for UBPC the dependence is greater, and γ hits zero before the utilization reaches 1.

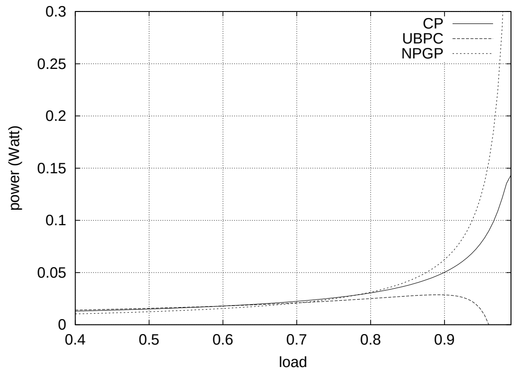

Fig. 5. For NPGP and CP, the power increases with the load. For UBPC, it initially increases slightly, but then drops to zero; this is due to the behavior of γ shown in Fig. 4.

dence with CP, and the signal quality decreases to zero before the utilization reaches 1. Hence, the UBPC scheme can result in a lower utilization compared to CP. On the other hand, γ for NPGP is independent of the load, since the price is independent of the load.

Finally, Fig. 5 shows the dependence of the transmission power on the load. For both the NPGP and CP schemes the power increases with the load. Indeed, the power for the CP scheme is higher compared to the NPGP scheme, since the signal quality for the former is higher, Fig. 4. For UBPC, it initially increases slightly, but then drops to zero; this is due to the behavior of γ shown in Fig. 4.

V. Conclusions

We have investigated models for resource control in wireless networks based on economics, in the case of traffic which has fixed-rate requirements but which can adapt it's signal quality. The model proposed in this paper is based on congestion pricing, and differs from other models proposed in the literature in that it considers the resource usage constraint in the uplink direction, and it does not differentiate users based on their distance from the base station.

Ongoing work considers the application of economic models for joint rate and signal quality control, congestion-sensitive downlink power control schemes, integration of congestion control mechanisms in wireless and wired networks, and resource control and service differentiation for wireless LANs based on 802.11.

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