

Optimal SIR-Based Power Control in 3G Wireless CDMA Networks ¹

S. Koskie and Z. Gajic

Wireless Information Network Laboratory (WINLAB)
Rutgers University, Piscataway NJ, USA.
{koskie,gajic}@winlab.rutgers.edu

Abstract

One aspect of the wireless communications power control problem that has received little attention is design of control algorithms that explicitly consider tradeoffs between transmit power SIR error costs. In this paper, we propose an novel optimal control algorithm for distributed power control in cellular communication systems. We assume that each mobile acts independently. The interference caused by the transmissions of mobiles in other cells is lumped with the background interference. We define a cost for each mobile that consists of a weighted sum of power, power update, and signal-to-interference ratio (SIR) error and obtain the corresponding optimal control law assuming the interference value does not change significantly from one measurement to the next. Simulation results demonstrate the superiority of the proposed controller to the power balancing algorithm in minimizing power usage.

1 Introduction

Because each user of a wireless communications system contributes to the interference affecting other users, effective and efficient power control strategies are essential for achieving both quality of service (QoS) and system capacity objectives.

Closed loop power control is used in wireless communication networks to compensate for time-varying channel characteristics, and to reduce mobile battery power consumption. The closed loop control structure for IS-95 (one of the currently implemented CDMA standards used in wireless networks) consists of an outer loop algorithm that updates the SIR threshold every 10 ms and an inner loop which calculates required powers based on SIR measurements updated at 800 Hz [20].

1.1 Review of the literature

The SIR balancing solution was originally derived for satellite communications by Aein [1] and Meyerhoff

[12], and adapted for wireless communications by Nettleton [13] and Zander [24] and [23]. SIR balancing attempts to minimize the combined power usage of all cochannel users by choosing a power vector that causes every mobile in the system to meet but not exceed the SIR threshold requirement. Other researchers have designed call admission and/or call dropping algorithms to address the cases when this is not possible

Another class of algorithms seek to solve a static optimization problem. The well known distributed constrained power control (DCPC) algorithm maximizes the minimum attained user SIR subject to maximum power constraints [6]. Other algorithms have been designed to minimize total power consumption in the presence of large-scale fading [25] or over a set of discrete available power levels [21]. Still others seek to minimize outage probability [15]

Dynamic optimization has been used to minimize total combined mobile power consumption by formulating power control for log-normal fading channels in a stochastic framework [7] and [8] as well as to adaptively optimize quantization of feedback SIR [19].

An alternative framework for developing power control algorithms is based on game theory [10] or economic formulations requiring the specification of a utility or cost function [2], [9] and [11]. Various utility functions have been suggested [9], [18], and [22]. The use of pricing to promote efficiency and fairness has been discussed extensively [16], and [17].

1.2 System Model

We consider here uplink (reverse link) power control. Although signature sequences are chosen orthogonal to one another, multipath distortion results in the presence of interference from other users to the signal received from a particular mobile at the base station. We designate by p_i the power transmitted by user i . We call the SIR of user i at the base station γ_i , and the background (receiver) noise at the base station η . In considering the signal transmitted by the i th user, we designate the effective attenuation of the interfering signal from the j th user to the base station by g_{ij} ,

¹This work was supported by National Science Foundation grant ANIR-0106857.

where $0 \leq g_{ij} \leq 1, \forall i$. In this formulation, interference at the base station to the i th user's signal is

$$I_i := \sum_{j \neq i} g_{ij} p_j + \eta. \quad (1)$$

and the SIR of the i th user's signal is

$$\gamma_i := \frac{g_{ii} p_i}{I_i} = \frac{g_{ii} p_i}{\sum_{j \neq i} g_{ij} p_j + \eta} \quad (2)$$

In the deterministic formulation of the power control problem, the noise η is treated as constant.

2 Discrete Time Dynamic Optimal Control

We give here a very brief introduction to the aspects of discrete time dynamic optimization used in the derivation. For a more detailed discussion see [3], [4], or [14].

Given a discrete time dynamic system whose behavior is described by

$$x[k+1] = f(x[k], u[k], k) \quad (3)$$

and a cost function

$$J[N] := g(x[N]) + \sum_{k=0}^{N-1} L(x[k], u[k], k) \quad (4)$$

we define the discrete Hamiltonian

$$H[k] := L(x[k], u[k], k) + \lambda^T[k+1] f(x[k], u[k], k). \quad (5)$$

A control sequence $u[k]$ that produces a stationary value of the cost function must satisfy the discrete state-costate equations

$$x[k+1] = f(x[k], u[k], k) \quad (6)$$

$$\lambda[k] = H_x^T[k] \equiv L_x^T[k] + f_x^T[k] \lambda[k+1] \quad (7)$$

with

$$H_u[k] \equiv L_u[k] + \lambda^T[k+1] f_u[k] = 0 \quad (8)$$

where $L_x[k] := L_x(x[k], u[k], k)$. This formulates the optimal control problem as a two-point boundary value problem with boundary conditions

$$x[0] = x_0 \quad (9)$$

$$\lambda[N] = g_x^T(x[N]). \quad (10)$$

The structure of the cost function $L(x[k], u[k], k)$ depends on the application. In our case, we are interested in deriving a control law for a discrete regulator based on a convex cost criterion. We can consider the finite or infinite horizon case. In the finite horizon case, an appropriate quadratic final cost is

$$g(x[N]) = \frac{1}{2} e_f^T Q_f e_f \quad (11)$$

where the final error e_f is defined by

$$e_f = M_f x[N] - e^{tar} \quad (12)$$

with M_f being a weighting matrix and e^{tar} the target value. (Our target SIR error is zero.) Cost functions $L(x[k], u[k], k)$ that are quadratic in the state and the input are often chosen for the tractability of the solutions to the state-costate equations (6) and (7).

When satisfied along the entire path, the following pair of conditions together constitute a sufficient condition for local optimality:

$$\begin{bmatrix} H_{xx} & H_{xu} \\ H_{xu}^T & H_{uu} \end{bmatrix} > 0 \quad (13)$$

$$H_{uu} > 0. \quad (14)$$

Solutions to optimal control problems may be obtained using either a forward or a backward computational method. Implementing backward methods in real-time is generally not feasible. We use a forward method to obtain controllers for the distributed mobile power control problem. As only the transient and not the steady state solutions depend on the initial conditions, the initial conditions can be arbitrarily chosen. For convenience, we choose initial powers to satisfy the static Nash optimality condition [10]. In fact, it has been shown [5] that, so long as the system is controllable and observable and the time-varying coefficients of the system have limits as time tends to infinity, the optimal control exists and is time-invariant, and further that the solution iteratively obtained is asymptotic to this optimal solution. Since our system satisfies these criteria, for any fixed set of transmitting mobiles in a cell, we can safely iteratively compute the solution.

3 Controller Derivation

We make a number of simplifications in order to propose a tractable controller for wireless power control. We assume that the interference does not change significantly from one measurement to the next and our mobile power controller does not consider the dynamics that may result from the response of other mobiles to changes in its own power. The resulting controllers will not, of course, be technically optimal, but we will show in simulation that given a cost function, they can provide a significant improvement over the power balancing algorithm.

3.1 Problem Formulation

We choose the SIR error as our system state and the power increment as the system input. Accordingly, defining the following quantities, (for simplicity of notation, we omit the subscript i from all quantities in

the remaining part of the paper),

$$\gamma[k] := \frac{gp[k]}{I[k]} \quad (15)$$

$$e[k] := \gamma[k] - \gamma^{tar} \quad (16)$$

$$u[k] := p[k+1] - p[k] \quad (17)$$

we have the system

$$\begin{aligned} e[k+1] &= \frac{g(p[k] + u[k])}{I[k+1]} - \gamma^{tar} \\ &= e[k] + \frac{gu[k]}{I[k]} + \frac{gp[k+1](I[k] - I[k+1])}{I[k]I[k+1]} \\ &\approx e[k] + \frac{gu[k]}{I[k]}. \end{aligned} \quad (18)$$

Note that the approximation in (18) is justified so long as the change in interference from one sample to the next is much smaller than the product of the two consecutive interference values. This assumption that the interference changes only slightly from one sampling instant to the next is commonly made in the communications literature since it is known that capacity and performance of wireless networks are limited by the presence of large interference values.

A consequence of (15) and (16) is that

$$p[k] = \frac{I[k](e[k] + \gamma^{tar})}{g}. \quad (19)$$

We will present optimal controllers for three separate cost functions:

$$J_I = \frac{1}{2} \sum_{k=0}^K (qe^2[k] + su^2[k]) \quad (20)$$

$$J_{II} = \frac{1}{2} \sum_{k=0}^K (qe^2[k] + 2rp[k] + su^2[k]) \quad (21)$$

$$J_{III} = \frac{1}{2} \sum_{k=0}^K (qe^2[k] + rp^2[k] + su^2[k]) \quad (22)$$

where J_I is understood to mean $J_I(e[k], u[k], K)$, *etc.* and in all cases we require $q, r, s > 0$. The first cost is very natural for the dynamic system described by (18); however, mobile battery life depends on the total power used – not just the power update. To address this deficiency we have formulated the second and third cost functions. Since power is a positive quantity, it is not necessary to square it in computing the cost and may only lead to excessively penalizing large powers. (Most users would settle for reduced battery life if that were the only way to get adequate SIR.) Note that by squaring the SIR error, we indirectly penalize excessive power consumption in the sense that if the SIR is better than we need for satisfactory QoS, we assign the same cost as if the SIR is too low by the same amount.

Because of the relationship (19) between power and SIR error, we can express the k th term of second cost in terms of SIR error, interference, and power update as

$$c_{II}[k] := qe^2[k] + \left(\frac{2rI[k]}{g}\right)e[k] + \left(\frac{2rI[k]}{g}\right)\gamma^{tar} + su^2[k]$$

and the k th term of the third cost as

$$c_{III}[k] := \tilde{q}[k]e^2[k] + 2\phi[k]\gamma^{tar}e[k] + \phi[k](\gamma^{tar})^2 + su^2[k]$$

where we have defined the quantities

$$\phi[k] := \frac{rI^2[k]}{g^2}, \quad (23)$$

and

$$\tilde{q}[k] := (q + \phi[k]). \quad (24)$$

From this we see that the effect of including the power terms in the cost is to rescale the weight on the quadratic term and add a linear term in SIR error. Accordingly we derive the optimal control laws corresponding to the second and third costs whereas that for the first can be found in many standard optimal control texts. For the purpose of determining necessary and sufficient conditions for local optimality, the linear terms can be subsumed into the quadratic terms by augmenting the state vector by one state which is constantly one. (This extra state is uncontrollable but asymptotically stable.) We will discuss this in more detail below.

In the following section, we derive, for fixed constant interference, the equations for the controller corresponding to the cost J_{II} and simply present the results that arise from similar derivations for the other two controllers.

3.2 Optimal Control — Linear Power Cost

With constant interference $I[k] = I$, $\forall k$, the discrete Hamiltonian corresponding to (21) is

$$\begin{aligned} H &= \frac{1}{2} \sum_{k=0}^K c_{II}[k] + \lambda[k+1]e[k+1] \\ &= \frac{1}{2} \sum_{k=0}^K c_{II}[k] + \lambda[k+1] \left(e[k] + \frac{gu[k]}{I} \right) \end{aligned} \quad (25)$$

where H is understood to mean $H(e[k], u[k], K)$. The condition that characterizes a stationary point

$$\frac{\partial H(e[k], u[k], K)}{\partial u[k]} = 0 \quad (26)$$

specifies the optimal power

$$u^*[k] = -\frac{g\lambda[k+1]}{sI}. \quad (27)$$

The multiplier sequence $\lambda[k]$ is chosen such that

$$\lambda[k] = \frac{\partial H(e[k], u[k], K)}{\partial e[k]} \quad (28)$$

which after solving for $\lambda[k+1]$ yields

$$\lambda[k+1] = \lambda[k] - qe[k] - \frac{rI}{g}. \quad (29)$$

To simplify the equations that follow, we define

$$\psi[k] := \frac{sI^2[k]}{g^2} \quad (30)$$

Now writing the Lagrange multiplier $\lambda[k]$ as ²

$$\lambda[k] = \mu[k]e[k] + \nu[k] \quad (31)$$

and substituting for $\lambda[k]$ in (29) yields

$$\lambda[k+1] = (\mu[k] - q)e[k] + \nu[k] - \frac{rI}{g} \quad (32)$$

but evaluating (31) at time step $k+1$ and substituting for $e[k+1]$ from (18) with $u[k] = u^*[k]$ yields

$$\begin{aligned} \lambda[k+1] &= \mu[k+1]e[k+1] + \nu[k+1] \\ &= \mu[k+1](e[k] - \psi^{-1}\lambda[k+1]) + \nu[k+1]. \end{aligned}$$

Isolating $\lambda[k+1]$ we have

$$\lambda[k+1] = \frac{\psi(\mu[k+1]e[k] + \nu[k+1])}{\psi + \mu[k+1]}. \quad (33)$$

Equating the right-hand sides of (32) and (33) and recalling that the $e[k]$ and $\nu[k]$ terms must separately sum to zero yields

$$\boxed{\mu[k+1] = \frac{\psi(\mu[k] - q)}{\psi - (\mu[k] - q)}} \quad (34)$$

and an expression for $\nu[k+1]$ in terms of $\nu[k]$, $\mu[k+1]$, $\gamma[k]$, and ψ . Substituting for $\mu[k+1]$ then yields the following expression for $\nu[k+1]$

$$\boxed{\nu[k+1] = \frac{\psi(g\nu[k] - rI)}{g(\psi - (\mu[k] - q))}}. \quad (35)$$

Using (32), we substitute for $\lambda[k+1]$ in (27) to obtain

$$\boxed{u^*[k] = -\frac{g}{sI} \left((\mu[k] - q)e[k] + \nu[k] - \frac{rI}{g} \right)}. \quad (36)$$

Next, we show that the second order sufficient conditions for local optimality are satisfied. In our implementation, we have required positive cost weights, so

²In the case of quadratic costs, it can be shown that the expression for $\lambda[k]$ should be linear in the state $e[k]$. See, for example, Bryson and Ho [4].

$H_{ee} = q > 0$ and $H_{uu} = s > 0$. $H_{eu} = 0$ so the matrix in (13) is block diagonal. Using the augmented state vector approach described above, we find that

$$H_{ee} = \begin{bmatrix} q & rI/g \\ rI/g & 2rI\gamma^{tar}/g \end{bmatrix} \quad (37)$$

This leads to the requirement that $2\gamma^{tar} > rI/g$, which can be viewed as prescribing a limit on allowable interference, $I < 2\gamma^{tar}g/r$, or providing a criterion for choosing an acceptable value of the power cost weight r , namely $r < 2\gamma^{tar}g/I$, in the presence of a given level of interference.

Finally, we note that to implement a controller based on (34), (35), and (36), we need the initial values for the controller states μ and ν . These are derived as follows. It can be shown that the boundary condition (10) implies the following expression for $\lambda[0]$,

$$\lambda[0] = 2q + \frac{q^2}{s} \left(\frac{g}{I[N]} \right)^2 e[0] + \frac{qr}{s} \left(\frac{g}{I[N]} \right) + \frac{rI[N]}{g} \quad (38)$$

From the form of (38) the initial controller states should be

$$\mu[0] = \frac{q^2}{s} \left(\frac{g}{I[N]} \right)^2 \quad (39)$$

$$\nu[0] = 2q + \frac{qr}{s} \left(\frac{g}{I[N]} \right) + \frac{rI[N]}{g}. \quad (40)$$

We use the static Nash powers to initialize our controller; however, any other initialization would change only the transient and not the steady-state values. Since the initial values of the controller states depend on the final values of the interferences, we need good initial estimates thereof.

The critical reader may have noticed that we mentioned using an augmented state vector $x[k] = [e[k], 1]$ in order to write the cost in terms of quadratic terms only. If we had used this augmented state vector in the derivation above, our Lagrange multiplier λ would have had two components; however, performing this more elaborate derivation, one finds that the second component of λ is superfluous, hence we have omitted it in order to make the presentation more readable.

3.3 Steady State Values

From (34) we see that the steady state value $\bar{\mu}$ of $\mu[k]$ must satisfy a quadratic equation

$$\bar{\mu}^2 - q\bar{\mu} - q\bar{\psi} = 0 \quad (41)$$

in which \bar{I} and $\bar{\psi}$ represent the steady state values of the interference and the parameter ψ respectively. Since $\bar{\mu}$ must be nonnegative and both q and $\bar{\psi}$ are positive we choose the positive square root

$$\bar{\mu} = \frac{1}{2}q \pm \frac{1}{2}\sqrt{q^2 + 4q\bar{\psi}}. \quad (42)$$

From (35) we determine that

$$\bar{\nu} = \frac{r\bar{I}\bar{\psi}}{g(\bar{\mu} - q)}. \quad (43)$$

3.4 Optimal Control — Quadratic Power Cost

A similar derivation yields for the third cost J_{III} ,

$$\mu[k+1] = \frac{\psi(\mu[k] - q - \phi)}{\psi - (\mu[k] - q - \phi)} \quad (44)$$

and

$$\nu[k+1] = \frac{\psi(\nu[k] - \phi\gamma^{tar})}{\psi - (\mu[k] - q - \phi)} \quad (45)$$

with

$$u^*[k] = -\frac{g}{sI} ((\mu[k] - q - \phi)e[k] + \nu[k] - \phi\gamma^{tar}).$$

The initial value of the Lagrange multiplier is

$$\lambda[0] = \left(2q + \frac{q^2g^2}{sI[N]}\right) e[0] + \frac{qr\gamma^{tar}}{s} + \phi[N]\gamma^{tar}$$

and the steady state values are

$$\bar{\mu} = \frac{1}{2}(q + \bar{\phi}) \pm \frac{1}{2}\sqrt{(q + \bar{\phi})^2 + 4q\bar{\psi}(q + \bar{\phi})} \quad (46)$$

and

$$\bar{\nu} = \frac{\gamma^{tar}\bar{\phi}\bar{\psi}}{\bar{\mu} - q - \bar{\phi}}. \quad (47)$$

The requirement that H_{ee} be positive definite reduces to the requirement that $q + \phi > \phi, \forall k$, so no restriction on acceptable interference or weight values arises.

3.5 Optimal Controller — Cheap Power

When we use the cost J_I , neglecting the cost of power, the controller obtained is characterized by

$$\mu[k+1] = \frac{\psi(\mu[k] - q)}{\psi - (\mu[k] - q)} \quad (48)$$

and

$$\nu[k+1] = \frac{\psi\nu[k]}{\psi - (\mu[k] - q)} \quad (49)$$

so that with ψ again defined by (30),

$$u^*[k] = -\frac{g((\mu[k] - q)e[k] + \nu[k])}{sI}.$$

The initial value of the Lagrange multiplier is

$$\lambda[0] = \frac{q(2\psi[N] + q)e[0]}{\psi[N] + q}$$

and the steady state value of μ is

$$\bar{\mu} = \frac{1}{2}q \pm \frac{1}{2}\sqrt{q^2 + 4q\bar{\psi}}. \quad (50)$$

Since (50) shows that $\bar{\mu} \neq 0$, inspection of (49) indicates that the steady state value $\bar{\nu}$ must be zero.

4 Simulation

The controllers were tested in simulation against the power balancing algorithm using a MATLAB script. For illustration purposes, a three mobile system was used. The attenuation matrix G had off-diagonal entries (corresponding to interference from other mobiles) two to three orders of magnitude smaller than the diagonal entries (mobile's own attenuation) which were chosen close to 1. Noise variance of 0.01 was used. These controllers were tested under a variety of conditions. Gain matrices were varied, as were number of mobiles and cost weights. In all cases, the SIR converged much faster than the power.

In Figure 1, examples of controller behavior are shown for the controller corresponding to linear power cost for a three-mobile example, without initialization of the controller states. It can be seen that *even without proper initialization, we have reasonably fast convergence*. In addition, this figure illustrates the effects of changing the SIR error cost weight. As expected we see that decreasing the SIR error cost weight leads to lower powers and larger SIR errors. The power and

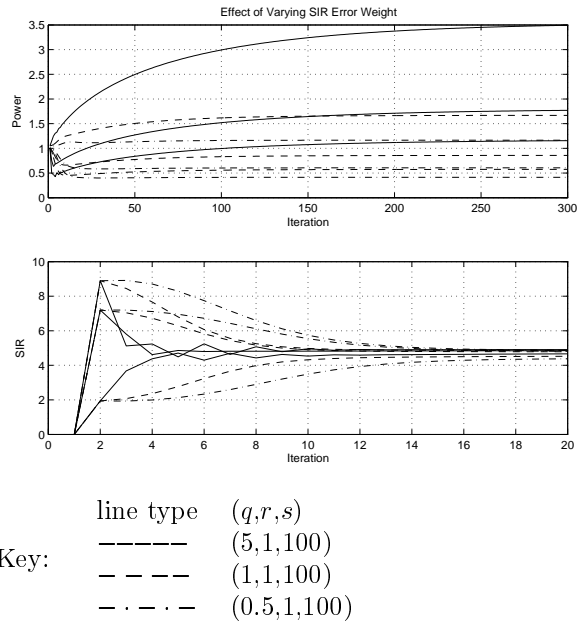


Figure 1: Controller corresponding to J_{II} , $\eta = 0.01$.

hence cost savings achievable using the optimal controller versus power balancing is seen in Figure 2. The advantage of the optimal controller over the power balancing controller is obvious.

4.1 Discussion

The physical constraints on system behavior limit the allowable values of the weights. We observed empirically that, in general, t should be two orders of magnitude larger than q . Decreasing r generally improves the

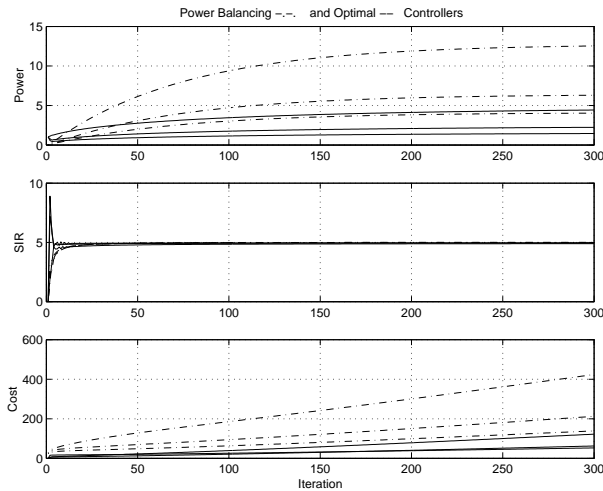


Figure 2: Comparison between power balancing (dashed lines) and optimal controller with linear power weight (solid lines), $\eta = 0.01$.

versatility (robustness) of the controller. This suggests that one might wish to have mobile power controllers with tunable weights for use under different interference conditions.

Controllers that weigh power cost in addition to power increment can yield significant power savings over those weighing only increment. The relation between the controllers for linear and quadratic power costs depends on the value of the power weight coefficient. If $r < 1$, then the quadratic cost formula assigns *less* weight to power than does the linear one, whereas if $r > 1$ the situation is reversed. Choice of a controller and specific weights would depend on experimentally determined parameters describing a particular cell site or cell site type. Factors that affect the choice would be typical number of active mobiles and typical power levels.

5 Conclusion

We have demonstrated that the suboptimal controller strategy outlined above has the potential to save power and improve QoS as compared with power balancing. Additional research topics of potential interest include choice of cost function and choice of interference update rate.

References

[1] J. M. Aein. Power balancing in systems employing frequency reuse. *COMSAT Technical Review*, 3(2):277–299, 1973.
 [2] T. Alpcan, T. Basar, R. Srikant, and E. Atman. CDMA uplink power control as a noncooperative game. *Proc. of the 40th IEEE Conf. on Decision and Control*, vol. 1, pp. 197–202, 2001.
 [3] A. E. Bryson, Jr. *Dynamic Optimization*. Addison-Wesley, Menlo Park, CA, 1999.
 [4] A. E. Bryson, Jr. and Y.-C. Ho. *Applied Optimal Control:*

Optimization, Estimation, and Control. Hemisphere Publishing, New York, 1975. revised printing.
 [5] A. Czornik. On discrete-time linear quadratic control. *Systems and Control Letters*, 36:101–107, 1999.
 [6] S. A. Grandhi and J. Zander. Constrained power control in cellular radio systems. *Proc., IEEE 44th Vehicular Technology Conf.*, vol. 2, pp. 824–828, 1994.
 [7] M. Huang, P. E. Caines, C. D. Charalambous, and R. P. Malhamé. Power control in wireless systems: a stochastic control formulation. *Proc., American Control Conf.*, pp. 750–755, 2001.
 [8] M. Huang, P. E. Caines, C. D. Charalambous, and R. P. Malhamé. Stochastic power control for wireless systems: Classical and viscosity solutions. *Proc., 40th IEEE Conf. on Decision and Control*, pp. 1037–1042, 2001.
 [9] H. Ji and C.-Y. Huang. Non-cooperative uplink power control in cellular radio systems. *Wireless Networks*, 4(3):233–240, 1998.
 [10] S. Koskie and Z. Gajic. A Nash game algorithm for SIR-based power control in 3G wireless CDMA networks. *Submitted*, 2002.
 [11] A. B. MacKenzie and S. B. Wicker. Game theory in communications: Motivation, explanation, and application to power control. *Proc., IEEE GLOBECOM '01*, pp. 821–826, 2001.
 [12] H. J. Meyerhoff. Method for computing the optimum power balance in multibeam satellites. *COMSAT Technical Review*, 4(1):139–146, 1974.
 [13] R. W. Nettleton and H. Alavi. Power control for a spread spectrum cellular mobile radio system. *Proc., IEEE Vehicular Technology Conf.*, pp. 242–246, 1983.
 [14] K. Ogata. *Discrete-Time Control Systems*. Prentice-Hall, Englewood Cliffs, NJ, 1987.
 [15] A. Ramesh and A. Chockalingam. Performance analysis of adaptive modulation with optimum power control in cellular systems. *Proc., IEEE Intl. Conf. on Personal Wireless Communications*, pp. 193–197, 2000.
 [16] C. U. Saraydar, N. B. Mandayam, and D. J. Goodman. Pricing and power control in a multicell wireless data network. *IEEE Journal, Selected Areas in Comm.*, 19:1883–1892, 2001.
 [17] C. U. Saraydar, N. B. Mandayam, and D. J. Goodman. Efficient power control via pricing in wireless data networks. *IEEE Trans. Communications*, 50(2):291–303, 2002.
 [18] V. Shah, N. B. Mandayam, and D. J. Goodman. Power control for wireless data based on utility and pricing. *Proc., Ninth IEEE International Symposium on Personal, Indoor and Mobile Radio Communications*, vol. 3, pp. 1427–1432, 1998.
 [19] H.-J. Su and E. Geraniotis. Adaptive closed-loop power control with quantized feedback and loop filtering. *IEEE Trans. Wireless Communications*, 1(1):76–86, 2002.
 [20] Telecommunications Industry Association. *TIA/EIA Interim Standard: Mobile Station–Base Station Compatibility Standard for Dual-Mode Wideband Spectrum Cellular System*, July 1993.
 [21] C. Wu and D. P. Bertsekas. Distributed power control algorithms for wireless networks. *IEEE Trans. Vehicular Technology*, 50(2):504–514, 2001.
 [22] M. Xiao, N. N. Shroff, and E. K. Chong. Utility-based power control in cellular wireless systems. *Proc., IEEE INFO-COM 2001*, pp. 412–421, 2001.
 [23] J. Zander. Distributed cochannel interference control in cellular radio systems. *IEEE Trans. Vehicular Technology*, 41(3):305–311, 1992.
 [24] J. Zander. Performance of optimum transmitter power control in cellular radio systems. *IEEE Trans. Vehicular Technology*, 41(1):57–62, 1992.
 [25] J. Zhang, E. K. P. Chong, and I. Kontoyiannis. Unified spatial diversity combining and power allocation for CDMA systems in multiple time-scale fading channels. *IEEE Journal on Selected Areas in Communications*, 19(7):1276–1288, 2001.