Resource Management in Mobile Communication Systems and Distributed Computer Systems

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Abstract. In computer and communication systems, competition and mutual interactions among users sharing system resources is frequently observed. Typical examples include the sharing of bandwidth in a wireless network or storage capacity in caching systems. In this context, we study different problems, such as load-balancing and proactive resource management in cellular networks, dynamic spectrum access and transmission power control, as well as distributed management of caching storage capacity. Due to mutual user interference, we have modeled and analyzed the aforementioned problems by means of economic theories and methodologies (e.g., game theory, auctions, markets, pricing), which provide useful mathematical tools for studying such situations. Different solution concepts have been considered (e.g., Nash equilibrium, or Nash bargaining solution, in cooperative contexts) and appropriate optimization methods have been applied to characterize such solutions and provide corresponding algorithmic methods to calculate the respective operating points (centrally or in a distributed manner).

Keywords: Mobile computing, Distributed systems, resource management, game theory, optimization theory.

1 Introduction

In the recent years, we are experiencing an exciting development in wireless and mobile communications. In almost every place in the world, voice or data services are available through 2G (Global System Mobile – GSM), or 3G (Universal Mobile Telecommunications System – UMTS) systems. Moreover, wireless local area networks (WLANs) cover various public spaces, such as airports, malls, companies and University campuses. This ever-increasing interest in wireless technologies has triggered a huge amount of research, as shown in the relevant literature.

In addition to wireless and mobile systems that enable Internet access, of particular importance are the Internet services per se, and their efficient operation. Currently, one of the most important and widely adopted Internet services is the World Wide

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Web (WWW). The impressive and ever-increasing use of the WWW service imposes the necessity for optimization in the access of informational content. Important is the role of WWW caching technology and content distribution networks (CDNs). Such technologies achieve a reduction in the delay of content delivery to users, as well as a reduction of network traffic, as the requested content is placed closer to the users.

This dissertation focuses on two basic axes: 1) resource management in mobile computing, and 2) resource management in distributed computer systems, emphasizing in the efficient operation of the WWW service. In what regards mobile computing, the following problems are studied: (i) Load balancing in wireless cellular networks, (ii) Handover blocking avoidance in wireless cellular networks, (iii) Dynamic spectrum access, and (iv) Power control. Regarding distributed computer systems and the WWW service, the study focuses on the avoidance of the monopolization of storage capacity by aggressive users, in order to achieve fair and efficient resource sharing. Specific problems that are studied are the following: (i) Distributed fair sharing of disk space capacity of an L1 caching proxy, and (ii) Management of storage capacity of caching hierarchies (case study L2 caching).

Notice that, typically, the decisions made by a user in a communication or computer system affect the other users, directly or indirectly. Such interactions, which strongly resemble real societies and social interaction problems, have already attracted the interest of mathematicians and economists, mostly in the previous century, resulting in the development of Game Theory [1]. Game Theory is a mathematical tool for studying situations with mutual interactions and conflicts of interests among selfish entities, termed players. Game Theory has been applied to various sciences, such as Economics, and Psychology. In the last decades, it has also been applied to problems relating to computer and communications systems.

In this dissertation, Game Theory as well as other economic concepts (e.g., auctions, pricing) are the basis for studying the examined resource management problems. Different solution concepts have been considered (e.g., Nash equilibrium, or Nash bargaining solution, in cooperative contexts) and compared. For the sake of brevity, here, we only present a representative contribution of the dissertation, the study of the power control problem in wireless networks.

2 CDMA Power Control

Wideband Code Division Multiple Access (WCDMA) has been widely adopted as the air interface technology for third generation (3G) networks [2]. WCDMA is interference limited: the multiple access interference, due to the simultaneous user transmissions in the same frequency, is the most significant factor in determining system capacity and quality of service (QoS).

A popular approach to the power control problem in CDMA networks is based on economic models [4], [12]. In such models, preferences for each user are represented by a utility function, which quantifies the level of user satisfaction. Each user seeks to maximize his utility in a selfish and distributed manner, and the game, potentially, settles at a Nash equilibrium (NE) [1].

A well-known, game theoretic, power control model has been introduced in [4]. Users select their transmission power, in a distributed manner, driven by a utility function, which quantifies the tradeoff between achieved throughput and consumed energy. The discussed game has a unique NE, which, however, is not quite efficient, as there are other power allocations yielding higher utility for all users. Specifically, it has been observed that if all users decrease their NE power by a given factor, a utility increase may be achieved for all of them.

An approach for urging users to reduce their transmission power is the introduction of pricing. To this end, the authors of several papers (e.g., [4], [5]) have proposed charging users proportionally to their transmission power. The users selected their power in order to maximize their net utility (utility minus cost). Such games are also known as "leader-follower" (Stackelberg) games [1], with the leader being the network (setting the pricing factor) and the follower the wireless users. Note, however, that a Pareto optimal operating point, still, could not be reached. Another important issue in pricing-based power control is that fairness tends to be undermined. For instance, in [4], at the NE with pricing, users that encounter high path loss are charged more and receive fewer resources, compared to users close to the BS.

Centralized power control may sometimes be quite beneficial for the wireless users, as more efficient operating points than the NE may be selected. In [6] and [7], the BS computes an "optimum" power allocation and then communicates it to the users. In both works, at the optimum power allocation, all users reach the BS with the same power, i.e., achieve equal signal-to-interference ratio (SIR). However, these works lack a formal analysis on the efficiency of the reported results. The Pareto optimality of the proposed solution is proven in [8].

In this paper, we are primarily concerned with the determination of fair and optimal operating points, in the power control problem, subject to individual user QoS constraints. We consider bandwidth-elastic, delay intolerant data services (e.g., voice, video, real time file transfers). We first assume a non-cooperative setting and derive the corresponding NE. Based on this game, we consider an alternative scheme, using the Nash bargaining solution (NBS) [3], which by definition results in Pareto optimal and fair outcomes. The NBS leads to a nonlinear optimization problem, which is shown to have a unique solution. For determining this solution we propose an appropriate numerical algorithm.

3 System Model

In this section, we describe the model adopted for studying the CDMA power control problem. Let $I = \{1, ..., N\}$ be the set of users who share the uplink bandwidth of a CDMA cell. User i controls his transmission power p_i in order to optimize a certain performance measure. We assume that p_i is chosen from $S_i = [0, +\infty)$. Let $\boldsymbol{p} = (p_1, \ldots, p_N)^T$ be a typical strategy profile vector in the strategy space $S = S_1 \times \ldots \times S_N$. We also assume that user i has certain QoS requirements in terms of lower and upper bounds on the achieved throughput. This is a natural assumption for real-time applications with adaptive coding, such as voice and video, which are tolerant to fluctuations in the available throughput.

We assume that the QoS (throughput) requirements of user i are expressed in terms of lower and upper bounds on the achieved SIR, $\gamma_{m,i}$ and $\gamma_{M,i}$, respectively ($\gamma_{m,i} < \gamma_{M,i}$)[1]. Let $\Gamma = \{ \boldsymbol{p} \in S : \gamma_{m,i} \le \gamma_i(\boldsymbol{p}) \le \gamma_{M,i} , \forall\, i \in I \}$ be the set of power allocations that result in feasible achieved SIR, where γ_i denotes the SIR of user i, as seen by the BS, and is defined as follows:

$$\gamma_i = \gamma_i(\boldsymbol{p}) = \frac{W}{R} \frac{h_i p_i}{\sum_{k \neq i} h_k p_k + \sigma^2} \tag{1}$$

W is the chip rate, R is the transmission rate, and W/R is the CDMA processing gain. h_i is the path loss from the mobile terminal to the BS, and σ^2 is the additive white Gaussian noise (AWGN) power at the receiver. Note that Γ is a convex and closed polyhedron in the space of power allocations, since the SIR constraints boil down to linear inequalities.

We assume that user i has a utility function u_i: $\Gamma \to \Re$ quantifying his level of satisfaction for using system resources. This function takes into account both the achieved QoS (throughput), as a result of the user's transmission power and the interference from the other users, and the energy consumption due to the transmission power, by measuring (approximately) the number of bits that are successfully received per unit of consumed energy. Although u_i is of similar form to the utility function in [4], our utility function is defined over the set of acceptable SIRs Γ, which is a subset of the power allocation space $S = S_1 \times \ldots \times S_N$. The utility function u_i of user i is

$$u_i(\boldsymbol{p}) = \frac{LR}{Mp_i} \left(1 - e^{-0.5\gamma_i}\right)^M \text{ (bits/Joule),} \tag{2}$$

where L is the length of the user frame, and M the length of the frame including headers ($M > L$). The term $\left(1 - e^{-0.5\gamma_i}\right)^M$ is an approximation to the probability of correct frame reception for asynchronous FSK modulation, assuming an additive Gaussian channel and no channel coding[2]. More details on the adopted utility function can be found in [4].

4 SIR-Constrained Non-Cooperative Power Control

In this section, we study the non-cooperative power control game. For the sake of brevity, we do not present all technical details, but only provide the analytical expres-

[1] In CDMA, the SIR at the receiver is directly coupled with the achieved bit-error-rate, and thus, throughput. However, their exact relation depends on the adopted modulation scheme. In this paper, to maintain the generality of the analysis and avoid mapping issues, we consider SIR as the only metric of the level of achieved QoS.

[2] This simplistic channel model is considered sufficient for modeling the power control game [4].

sion of the NE[3] (a power allocation where, given the power levels of the other users, no user can improve his utility by making individual changes to his transmission power – a stable operating point). The NE of the game, in SIR terms is given as follows [8]:

$$\gamma_i^* = \begin{cases} \gamma_{m,i}, & \gamma^* \le \gamma_{m,i} < \gamma_{M,i} \\ \gamma^*, & \gamma_{m,i} < \gamma^* \le \gamma_{M,i} \\ \gamma_{M,i}, & \gamma_{m,i} < \gamma_{M,i} < \gamma^* \end{cases} \tag{3}$$

The term γ^* is the unique non-zero solution of (4).

$$0.5M\gamma_i + 1 = e^{0.5\gamma_i} \tag{4}$$

By solving the linear system of SIR equations (see (1)), for $\gamma_i = \gamma_i^*$, $\forall\ i \in\ I$., we also obtain the NE power allocation, as follows:

$$q_i = \frac{\sigma^2}{\left(\frac{W}{R\gamma_i}+1\right)\left(1-\sum_{k=1}^{N}\left(\frac{W}{R\gamma_k}+1\right)^{-1}\right)},\ \forall\ i \in I, \tag{5}$$

where $q_i = h_i p_i$ is the power with which user i reaches the BS.

From (5), we note that, for a power allocation to be feasible, the following constraint should be satisfied:

$$\sum_{k=1}^{N}\left(\frac{W}{R\gamma_k}+1\right)^{-1} < 1 \tag{6}$$

Otherwise, the power (as determined by (5)) becomes infinite or negative. Constraint (6) expresses the capacity limitation of a CDMA system (also termed *pole capacity*), and can be easily adopted as the basis for a simple call admission control (CAC) mechanism.

The NE of a game is a natural and stable operating point of the system. Apart from stability, however, another important attribute is efficiency. A commonly accepted notion of efficiency is Pareto optimality. A point is Pareto optimal, if it is impossible to find a point, other than the Pareto optimum, which yields strictly superior utility for all users simultaneously, as stated formally below.

Definition 1 (*Pareto optimality*): The point $\boldsymbol{u} \in U$, where U is the set of achievable utilities, is said to be Pareto optimal if for each $\boldsymbol{u}' \in U$, $\boldsymbol{u}' \ge \boldsymbol{u}$, then $\boldsymbol{u}' = \boldsymbol{u}$.

The NE power allocation of the SIR-constrained power control game is, typically, not Pareto optimal [9]. Hence, a more efficient mechanism, than the non-cooperative game, is needed.

[3] As shown in [9] there is a unique NE in the power control game.

5 SIR-Constrained Arbitrated Power Control

In this section, we study a centralized power control scheme aiming at achieving more efficient system performance, compared to the non-cooperative game setting. Our goal is to provide Pareto optimal solutions (see Definition 1). To select one Pareto optimal point, we propose the bargaining solution introduced by Nash [3].

5.1 The Nash Bargaining Solution

Here, we provide a brief overview of the NBS and the corresponding formulations. User i, apart from his utility function u_i defined over Γ, has also a utility u_i^0, which corresponds to the maximum utility that he can achieve without cooperation (status quo utility), i.e., the NE utility. The arbitrated solution should always yield superior utility to u_i^0 for user i to cooperate. Hence, here, $u_i^0 = u_i(\boldsymbol{p}^*)$, where $\boldsymbol{p}^*$ is the NE power allocation vector. We will refer to $\boldsymbol{u^0} = (u_1^0, \ldots, u_N^0)$ as the status quo of the game, or disagreement point. Below we define the NBS.

Definition 2: A mapping F: $G \to \Re^N$, where G denotes the set of achievable utility with respect to the disagreement point $\boldsymbol{u^0}$, is said to be a NBS, if the following hold:

1) $F(U, \boldsymbol{u^0}) \in U_0$, where U_0 is the set of achievable utilities that are superior to the status quo.
2) $F(U, \boldsymbol{u^0})$ is Pareto optimal.
3) F satisfies the linearity axiom: if $\boldsymbol{\varphi}$: $\Re^N \to \Re^N$, $\boldsymbol{\varphi}(\boldsymbol{u}) = \boldsymbol{u}'$ with $u'_j = a_j u_j + b_j$, $a_j > 0$, $j = 1, \ldots, N$, then $F(\boldsymbol{\varphi}(\boldsymbol{u}), \boldsymbol{\varphi}(\boldsymbol{u^0})) = \boldsymbol{\varphi}(F(\boldsymbol{u}, \boldsymbol{u^0}))$.
4) F satisfies the irrelevant alternatives axiom: if $V \subset U$, $(V, \boldsymbol{u^0}) \in G$ and $F(U, \boldsymbol{u^0}) \in \mathrm{V}$, then $F(U, \boldsymbol{u^0}) = F(V, \boldsymbol{u^0})$.
5) F satisfies the symmetry axiom: if i) $\boldsymbol{u} \in U$, ii) $u^0_i = u^0_j$, and iii) if $(u_1, \ldots, u_i, \ldots, u_j, \ldots, u_N) \in U$, then $(u_1, \ldots, u_j, \ldots, u_i, \ldots, u_N) \in U$, it follows that $F(U, \boldsymbol{u^0})_i = F(U, \boldsymbol{u^0})_j$ for $i, j \in \{1, \ldots, N\}$.

The first and second items are the axioms regarding the superiority of the solution to the status quo of the game and the requirement for Pareto optimality, respectively. Items (3), (4), and (5) are often referred to as axioms of fairness.

The solution of Nash, which satisfies all of the above axioms, is achieved at the point where the product of surplus utilities beyond the status quo is maximized, subject to the constraint that the utility of each user must be superior to his status quo utility. For the power control problem studied in this paper, the discussed point is the solution of the following problem.

$$\max_{\boldsymbol{p}} \prod_{j=1}^{N} \left(u_j(\boldsymbol{p}) - u_j^0\right), \quad \boldsymbol{p} \in Q_0, \; Q_0 = \{\boldsymbol{r} \in \Gamma : \boldsymbol{u}(\boldsymbol{r}) > \boldsymbol{u}_0\}$$

5.2 Properties of the Nash Bargaining Solution

Here, we study the properties of the optimization problem that leads to the NBS of the power control game. Specifically, we prove that the studied problem has a unique solution, which is essential for applying a gradient-based numerical method for the determination of the solution.

Consider a linear utility transformation $\boldsymbol{\varphi}$: $\Re^N \rightarrow \Re^N$, where $\boldsymbol{\varphi}(\boldsymbol{u}) = \boldsymbol{v}$, $v_i = (1/h_i)u_i$, $\forall\, i \in I$. It is easy to see that the transformed utility functions v_i are of the form

$$v_i(\boldsymbol{q}) = \frac{LR}{Mq_i}\left(1 - e^{-0.5\gamma_i}\right)^M , \qquad \textbf{(7)}$$

where $q_i = h_i p_i$. With this transformation, which does not affect the solution, we consider only received power at the BS. In this way, the BS may solve for the received powers of the users (without having to be aware of the path loss of every user), and, then, communicate such (target) powers to the users, which, in turn, shall adjust their transmission power, according to their estimated path loss. Specifically, the BS needs to solve the following optimization problem:

$$(P) \quad \max_{\boldsymbol{q}} f(\boldsymbol{q}), \;\; f(\boldsymbol{q}) = \prod_{j=1}^{N}\left(v_j(\boldsymbol{q}) - v_j^0\right), \quad \boldsymbol{q} \in Q_0$$

Note that the utility function $v_i(\cdot)$ of user i is quasiconcave over the set Γ.

Lemma 1: The utility function v_i: $\Gamma \rightarrow \Re$, for user $i \in I$, is quasiconcave.

Proof: See [9]. ■

An important issue in the study of an optimization problem is also the structure of the constraint set. The constraint set Q_0 composed of the power allocations that result in (i) acceptable SIR, and (ii) utilities that are superior to the status quo and is convex.

Lemma 2: The set of power allocations Q_0 that are Pareto dominant to the status quo power allocation is convex.

Proof: See [9]. ■

Another important issue is the form of the objective function. The objective function $f(\boldsymbol{q})$ of problem (P) is quasiconcave and problem (P) has a unique solution.

Theorem 1: The objective function $f(\boldsymbol{q})$ of problem (P) is quasiconcave over the set Q_0. Moreover, problem (P) has a unique solution.

Proof: See [9]. ■

From the above, we, thus, conclude that we may use a gradient-based approach to determine numerically the pursued (unique) solution of problem (P).

5.3 Determination of the Nash Bargaining Solution

As a first step for solving problem (P), we define problem (P'), which derives from (P), by taking the logarithmic transformation of its objective function:

$$(P') \quad \max_{\boldsymbol{q}} g(\boldsymbol{q}), \;\; g(\boldsymbol{q}) = \sum_{j \in 1}^{N} \ln\left(v_j(\boldsymbol{q}) - v_j^0\right), \quad \boldsymbol{q} \in Q_0 .$$

Note that the objective function of problem (P'), $g = \ln(f)$, is quasiconcave as a composition of the increasing logarithm function $\ln : \Re_+ \rightarrow \Re$ and the quasiconcave function $f : \Re^N \rightarrow \Re$; thus, it has a unique maximum. Moreover, the global maximum $\tilde{\boldsymbol{q}}$ of the objective function $f(\cdot)$ (i.e., solution of problem (P)) is also the global maximum of the objective function $g(\cdot)$ (i.e., solution of problem (P')) [10], i.e., problems (P) and (P') are equivalent[4].

We propose an iterative algorithm for solving problem (P') based on the *conditional gradient method* [11]. This method can be applied when the objective function (here $g(\cdot)$) is continuously differentiable and the constraint set is nonempty, closed, and convex. In the considered problem, the constraint set Q_0 is nonempty. Specifically, (i) set Γ is never empty, as guaranteed by the CAC mechanism, and (ii) set Q_0 ($\subseteq \Gamma$) is not empty, i.e., a Pareto dominant power allocation to the NE can be typically found (see discussion in [9]). However, set Q_0 may not be closed due to the strict utility inequalities that define it. Nevertheless, this does not affect the convergence of the proposed algorithm, as the method that we introduce guarantees that the point derived, after every iteration, stays always within the constraint set.

The conditional gradient method starts with a feasible vector $\boldsymbol{q}^{(0)}$ and generates a sequence of feasible vectors $\{\boldsymbol{q}^{(n)}\}$ according to

$$\boldsymbol{q}^{(n+1)} = \boldsymbol{q}^{(n)} + a^{(n)}\boldsymbol{d}^{(n)},$$

where $a^{(n)}$ is the stepsize, and $\boldsymbol{d}^{(n)}$ is the (gradient-related) direction vector, at step n.

The problem of determining a feasible ascent direction, given a feasible vector $\boldsymbol{q}^{(n)}$, at step n, is to find a vector $\boldsymbol{d}^{(n)}$, such that $\boldsymbol{q}^{(n)} + a\boldsymbol{d}^{(n)}$ is feasible, for all $a > 0$ that are sufficiently small, and

$$\nabla g(\boldsymbol{q}^{(n)})^{\mathrm{T}} \cdot \boldsymbol{d}^{(n)} > 0.$$

A straightforward way to generate a feasible direction $\boldsymbol{d}^{(n)}$, from a point $\boldsymbol{q}^{(\mathrm{n})}$, is to find the remotest point of the constraint set (Q_0) along the gradient direction, i.e.,

$$\overline{\boldsymbol{q}}^{(n)} = \arg\max_{\boldsymbol{w} \in Q_0} \nabla g(\boldsymbol{q}^{(n)})^T \cdot \left(\boldsymbol{w} - \boldsymbol{q}^{(n)}\right),$$

and set $\boldsymbol{d}^{(n)} = \overline{\boldsymbol{q}}^{(n)} - \boldsymbol{q}^{(n)}$ [11]. Note that the determination of point $\overline{\boldsymbol{q}}^{(n)}$ is quite simple, when the constraint set is defined by linear constraints. However, in our case, the constraint set Q_0 includes nonlinear constraints as well (each user must receive strictly superior utility to the status quo utility).

In order to cope with the nonlinearity of set Q_0, we propose a two-phase feasible direction finding procedure. Firstly, we consider only the linear constraints, i.e., the SIR constraints that form the convex polyhedron Γ. Specifically, having reached a feasible vector $\boldsymbol{q}^{(n)}$, we find $\overline{\boldsymbol{q}}^{(n)}$, the remotest point of set Γ, along the gradient direction. If $\overline{\boldsymbol{q}}^{(n)}$ is not feasible, i.e., there is at least one user that does not enjoy higher utility to the status quo, we take advantage of the fact that set Q_0 is convex (Lemma 2), and that $Q_0 \subseteq \Gamma$, in order to find another feasible point $\overline{\boldsymbol{q}}'^{(n)}$.

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[4] This transformation of (P) to (P') makes the numerical determination of the pursued solution easier, as it is more convenient to handle a sum, rather than a product of functions, e.g., when computing their derivative.

Observe that, if $\boldsymbol{q}^{(n)} \in Q_0$, but $\overline{\boldsymbol{q}}^{(n)} \notin Q_0$, one can find a point $\overline{\boldsymbol{q}}'^{(n)}$ on the line segment connecting points $\boldsymbol{q}^{(n)}$ and $\overline{\boldsymbol{q}}^{(n)}$ such that $\overline{\boldsymbol{q}}'^{(n)} \in Q_0$. Hence, the second phase of the direction finding procedure is to locate point $\overline{\boldsymbol{q}}'^{(n)}$. Point $\overline{\boldsymbol{q}}'^{(n)}$ can be easily calculated through a bisection-based procedure [9]. The direction $\boldsymbol{d}^{(n)}$ at step n is then $\boldsymbol{d}^{(n)} = \overline{\boldsymbol{q}}'^{(n)} - \boldsymbol{q}^{(n)}$. Fig. 1 outlines the two-phase direction finding procedure, in a two-dimensional space, for presentation purposes.

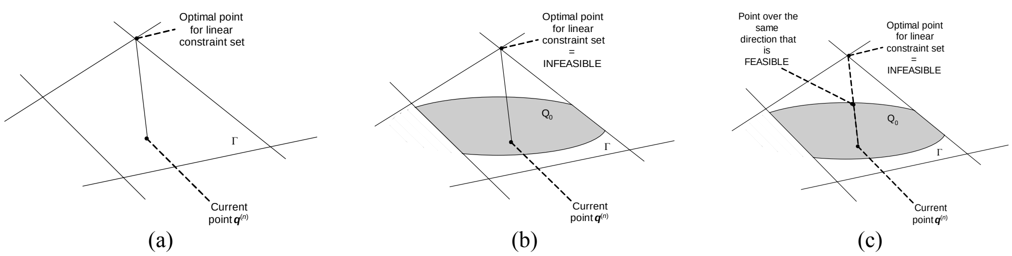

Fig. 1. Two-Phase direction selection procedure. (a) Optimal direction subject to linear SIR constraints only, (b) The optimal direction subject to the linear constraints is not feasible (i.e., it lies outside set Q_0), (c) the initial direction is scaled in order to become feasible.

In the proposed iterative procedure, at each step, the stepsize is readjusted, based on the *Armijo* rule [11], in order to accelerate convergence. According to the discussed rule, the stepsize $a^{(n)}$ is chosen not only to produce a positive improvement in the objective function, but a sufficiently large improvement [9].

6 Numerical Results

In this section, we provide results from the performance analysis of the proposed NBS-based power control scheme. **Table 1** gives the values of the system parameters used throughout our analysis; these values have been adopted from [2], [4] and [12]. The SIR bounds of each user, $\gamma_{m,i}$ and $\gamma_{M,i}$, are independent and uniformly distributed random variables in the interval $[\gamma_{min}, \gamma_{thres}]$ and $[\gamma_{thres}, \gamma_{max}]$, respectively; $\gamma_{thres} \in [\gamma_{min}, \gamma_{max}]$ is a parameter. Here, we present results for the scenario, where $\gamma_{thres} = 15$. The random SIR bounds of the users are shown in **Table 2**.

Table 1. The list of parameters for the simulated single-cell CDMA system.

M, total number of bits per frame	80
L, number of information bits per frame	64
W, spread spectrum bandwidth	3.84×10^6 Hz
R, bit rate	30×10^3 b/s
$\boldsymbol{\sigma^2}$, AWGN power at the receiver	2×10^{-13} W
modulation technique	non coherent FSK
$\boldsymbol{p_{max}}$, maximum power constraint	600 mW

Table 2. User SIR requirements in the simulations.

User, i	1	2	3	4	5	6	7	8	9	10
$\gamma_{m,i}$	4.67	5.72	14.26	10.83	14.81	6.67	6.40	8.38	6.51	1.42
$\gamma_{M,i}$	28.27	26.01	33.73	45.63	45.99	36.95	44.68	43.26	48.66	48.38

The metrics used for the evaluation of the proposed scheme are the following: (1) achieved utility, $v_i(\boldsymbol{q})$, (2) power with which users reach the BS, q_i, (3) achieved SIR, γ_i, and (4) maximum achieved cell radius, $d_{i,max}$. Note that the utility $v_i(\boldsymbol{q})$ denotes the utility of user i, regardless of the associated path loss h_i (see (7)). The maximum cell radius, $d_{i,max}$, is determined as the maximum distance from which the user may reach the BS transmitting with the power that corresponds to the NE or the NBS of the game. We assume a simple path loss model, i.e., $h_i = K_1/d_i^4$, where $K_1 = 0.097$ [5], and d_i denotes the distance between user i and the BS. Given that a user may transmit with a power bounded by a maximum value p_{max} (see Table 1), the distance from which user i is capable of reaching the BS is also bounded, and given as follows:

$$d_{i,\max} = \sqrt[4]{\frac{K_1 p_{\max}}{q_i}}, \qquad \textbf{(8)}$$

where q_i is equal to q_i^* or $\tilde{q}_i$ for the NE or the NBS point, respectively.

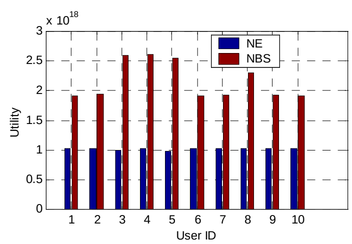

Fig. 2. Utility level at the NE and the NBS.

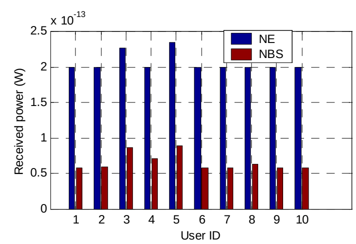

Fig. 3. Received power at the NE and the NBS.

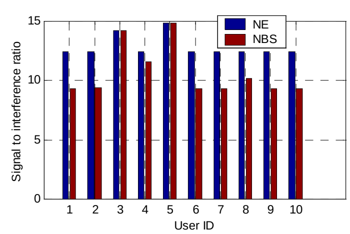

Fig. 4. SIR at the NE and the NBS.

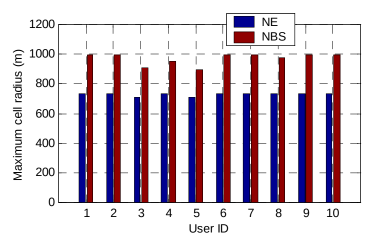

Fig. 5. Maximum cell radius at the NE and the NBS.

Fig. 2 shows the achieved levels of utility of each user at the NE and NBS. Owing to the Pareto dominance of the NBS over the NE of the game, NBS utility values are expected to be larger than the NE ones. Indeed, we observe that the proposed NBS-based scheme attains significantly larger utility values compared to the non-cooperative scheme. Fig. 3 shows the values of the received power from each user at the BS for the NE and NBS. Observe that the received power at the NE is significantly higher than the corresponding received power at the NBS. In other words, operating at the NBS point may yield significant energy savings.

Fig. 4 shows the achieved SIR results. Note that the NBS SIR is inferior to the NE SIR. Note, however, that this deterioration is rather minor compared to the respective energy savings achieved due to the corresponding transmission power reduction (see Fig. 3). Fig. 5 shows the maximum cell radius results, where we observe a considerable increase in the maximum cell radius, at the NBS compared to the NE.

Another important issue is the achieved performance versus the number of users. We assume that the number of users ranges between two and eleven (the capacity limit of the system described in **Table 1**), and that all users have identical SIR requirements. We examine the same metrics as above (i.e., achieved utility, received user power at the BS, achieved SIR, and maximum cell radius). In Figures 6, 7, 8, and 9, we observe that the NBS-based scheme outperforms the NE-based one for every user population. Also, observe that as the number of users increases and the system reaches its capacity limits, the performance improvements become more significant.

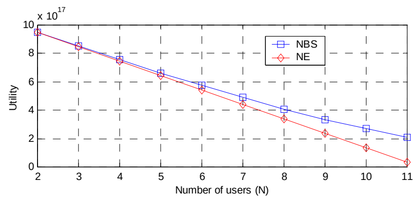

Fig. 6. Utility level at the NE and the NBS.

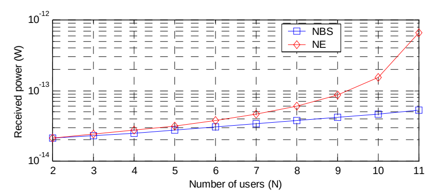

Fig. 7. Received power at the NE and the NBS.

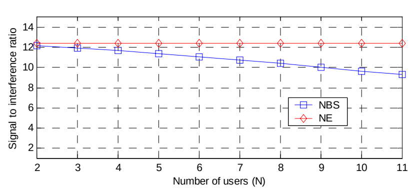

Fig. 8. SIR at the NE and the NBS.

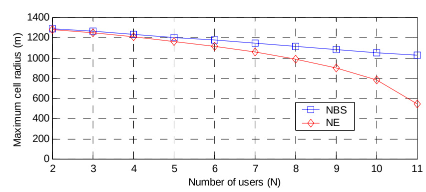

Fig. 9. Maximum cell radius at the NE and the NBS.

7 Conclusions and Future Work

In this dissertation, we have studied a set of resource management problems in wireless-mobile and distributed computer systems. The basic axis of the dissertation has been the methodology for the modeling and solution of the discussed problems, where competition and mutual interference is their common characteristic. Specifically, we have used Game Theory and other economically inspired methodologies for their mathematical modeling, which led in turn to clear optimization targets, regarding the operation of each of the studied systems.

An indicative example is the CDMA power control problem, presented in the previous sections. We have formulated the problem as a non-cooperative game, and, then, used the NBS, which (contrary to the NE) provides Pareto optimal and fair (according to the NBS fairness definition) outcomes. The NBS is the solution of an optimization problem, for the determination of which we have introduced a numerical algorithm.

Future research directions may derive based on each different problem studied in the context of the dissertation. For instance, regarding the CDMA power control presented here, in the future, we would like to extend our NBS-based solution to multicell environments. Moreover, it would be interesting to apply alternative cooperative solutions, apart from the NBS, as, for example, Shapley value and compare the benefit stemming from each approach to the discussed problem.

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