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Resource-Constrained Networks

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Energy-Efficient Resource Allocation in Wireless Networks

[An overview of game-theoretic approaches]

Future wireless networks are expected to support a variety of services with diverse quality-of-service (QoS) requirements. For example, a mixture of delay-sensitive applications (e.g., voice and video teleconferencing) and delay-tolerant ones (e.g., Web browsing and file downloading) must be supported. Given that the two principal wireless network resources, i.e., bandwidth and energy, are scarce, the main challenge in designing wireless networks is to use network resources as efficiently as possible while providing the QoS required by the users.

Game-theoretic approaches to radio resource allocation have recently attracted much attention and will be the focus of this article. We will show that game theory can be used as a unifying framework to study radio resource management in a variety of wireless networks

with different service criteria. Our focus will be on infrastructure networks where users transmit to a common concentration point such as a base station in a cellular network or an access point. Since most of the terminals in a wireless network are battery-powered, energy efficiency is crucial to prolonging the life of the terminals.

Also, in most practical scenarios, distributed algorithms are preferred over centralized ones. Centralized algorithms tend to be complex and not easily scalable. Therefore, throughout this article, we focus on distributed algorithms with emphasis on energy efficiency. Using a game-theoretic framework, we demonstrate the impact of advanced signal processing on energy efficiency and network capacity. The tradeoffs among throughput, delay, network capacity and energy efficiency are also discussed. The ideas presented in this article can also be applied to wireless ad hoc networks, however, the topic is beyond the scope of this article (see [1] for applications of game theory to ad hoc networks).

It should be noted that, recently, tools from optimization theory have also been employed to study resource allocation in wireless networks using the network utility maximization framework proposed in [2] (see, for example, [3]). While there is considerable overlap between the game-theoretic and optimization-theoretic approaches, game theory tends to focus on the multiuser competitive nature of the problem and on the users' interaction.

The rest of this article is organized as follows. In the following sections, we describe how game theory can be used for studying radio resource management in wireless networks and discuss the choice of the utility function. Then we present a family of power control games for energy-efficient resource allocation in wireless code-division multiple-access (CDMA) networks and give discussions and conclusions.

GAME THEORY FOR RADIO RESOURCE MANAGEMENT

Game theory is a mathematical tool for analyzing the interaction of two or more decision makers. Game theory has been used in a variety of fields such as economics, political science, and biology [4]. A (strategic) game consists of three components: a set of players, the strategy set for each player, and a utility (payoff) function for each player measuring the degree of happiness of the player [5]. Recently, game theory has also been used in telecommunications, particularly wireless communications (see for example [6]–[9]). The users' interaction in a wireless network can be modeled as a game in which the users' terminals are the players in the game competing for network resources (i.e., bandwidth and energy). Any action taken by a user affects the performance of other users in the network. Game theory is the natural tool for studying this interaction.

Since our focus in this article is on distributed schemes, we will concentrate on noncooperative games. Let $\mathcal{G} = [\mathcal{K}, \{\mathcal{A}_k\}, u_k]$ represent a game where $\mathcal{K} = \{1, \cdots, K\}$ is the set of players/users, $\mathcal{A}_k$ is the set of actions (strategies) available to user k, and u_k is the utility (payoff) function for user k. In a non-

cooperative game, each user seeks to choose its strategy in such a way as to maximize its own utility, i.e.,

$$\max_{a_k \in \mathcal{A}_k} u_k \quad \text{for} \quad k = 1, \cdots, K. \tag{1}$$

> **GAME THEORY TENDS TO FOCUS ON THE MULTIUSER COMPETITIVE NATURE OF THE PROBLEM AND ON THE USERS' INTERACTION.**

For such a game, we first need to define two important concepts, namely, a Nash equilibrium (NE) and Pareto optimality [5].

DEFINITION 2.1
An NE is a set of strategies, $(a_1^*, \cdots, a_K^*)$, such that no user can unilaterally improve its own utility, i.e.,

$$u_k(a_k^*, a_{-k}^*) \geq u_k(a_k, a_{-k}^*) \quad \text{for all}$$
$$a_k \in \mathcal{A}_k \quad \text{and} \quad k = 1, \cdots, K, \tag{2}$$

where $a_{-k}^* = (a_1^*, \cdots, a_{k-1}^*, a_{k+1}^*, \cdots, a_K^*)$.

An NE is a stable outcome of $\mathcal{G}$. At NE, no user has any incentive to change its strategy.

DEFINITION 2.2
A set of strategies, $(\tilde{a}_1, \cdots, \tilde{a}_K)$ is Pareto-optimal if there exists no other set of strategies for which one or more users can improve their utilities without reducing the utilities of other users.

It should be noted that our focus throughout this article is on pure strategies. However, one could also allow for the users to have mixed strategies. In such a case, each user assigns a probability distribution to its pure strategies, and then it chooses a pure strategy based on the probability distribution. A noncooperative game may have no pure-strategy NE, one equilibrium, or multiple equilibria. Also, in many cases, an NE may not be Pareto-efficient (Pareto-optimal).

As an example, consider the following two-player game called the *Prisoner's Dilemma* [4]. The two players are two prisoners that have been arrested for a joint crime. They are taken into separate rooms and given the options to either confess (C) to the crime or not confess (NC). Each prisoner is told that if they both confess, each gets a light sentence (i.e., payoff of -1). If neither confesses, both will go free (i.e., payoff of 0). If one of them confesses and the other one does not, the confessor will get a reward (i.e., payoff of $+1$) and the other prisoner will get a heavy sentence (i.e., payoff of -2). The actions and the corresponding payoffs of the players are shown in Figure 1. Since the two prisoners are in separate rooms and hence are not able to cooperate, the payoff-maximizing selfish strategy for each of them is to confess. It can easily be verified that (C, C) is the unique NE of this game. Furthermore, this equilibrium is not Pareto-efficient since choosing (NC, NC) would result in a larger payoff for both players. However, this would require cooperation between the two prisoners. Hence, it is evident from this example that there is a clear conflict between individual rationality and social welfare.

In this article, we provide an overview of game-theoretic

approaches to energy-efficient resource allocation in wireless networks. Consider the uplink of a direct-sequence CDMA (DS-CDMA) network, where each user wishes to locally and selfishly choose its action in such a way as to maximize its own utility while satisfying its QoS requirements. Depending on the situation, the actions open to each user in trying to maximize its own utility can be, for example, the choice of its transmit power, transmission rate, modulation, packet size, multiuser receiver, multiantenna processing algorithm, or carrier allocation strategy. The strategy chosen by a user affects the performance of other users in the network through multiple-access interference. There are several important questions to ask regarding game $\mathcal{G}$. First of all, what is a reasonable choice of utility function? Secondly, given the utility function, what strategy must a user choose in order to maximize its own utility (i.e., best-response strategy)? If every user in the network selfishly and locally picks its best-response strategy, will there be a steady-state solution where no user can unilaterally improve its utility (i.e., NE)? If such a steady-state solution exits, is it unique? How does the performance of such a noncooperative approach compare with a cooperative scheme?

Let us consider the uplink of a synchronous DS-CDMA network with K users. For the sake of simplicity, we focus on a synchronous CDMA system. Many of the results presented in this article can be generalized to asynchronous systems as well. Assuming quasi-static fading, the signal received by the uplink receiver (after chip-matched filtering) sampled at the chip rate over one symbol duration can be expressed as

$$\mathbf{r} = \sum_{k=1}^{K} \sqrt{p_k h_k}\, b_k \mathbf{s}_k + \mathbf{w}, \qquad (3)$$

where $p_k, h_k, b_k,$ and $\mathbf{s}_k$ are the transmit power, channel gain, transmitted bit, and spreading sequence of user k, respectively, and $\mathbf{w}$ is

> **THE CHOICE OF THE UTILITY FUNCTION HAS A GREAT IMPACT ON THE NATURE OF THE GAME AND HOW THE USERS CHOOSE THEIR ACTIONS.**

the noise vector, which includes other-cell interference and is assumed to be Gaussian with mean $\mathbf{0}$ and covariance $\sigma^2 \mathbf{I}$. Throughout this article, we study distributed resource allocation in such a wireless network by presenting several (noncooperative) power control games in which users choose their strategies in such a way as to maximize their utilities. The emphasis will be mainly on energy efficiency. It should be noted that in the power control games under consideration, the actions available to the users are not limited to the choice of transmit power. Depending on the situation, the users may also choose their transmission rates, modulation schemes, packet sizes, multiuser receivers, multiantenna processing algorithms, or carrier allocation strategies. Furthermore, cross-layer resource allocation can be achieved by expanding the strategy sets of the users over multiple layers in the OSI protocol stack or by defining the users' utility functions such that performance measures across multiple layers are included.

UTILITY FUNCTION
Based on the discussions in the previous section, the choice of the utility function has a great impact on the nature of the game and how the users choose their actions. For resource allocation in wireless data networks, several different utility functions have been used in the literature.

When maximizing the spectral efficiency is the main goal, it is common to define the user's utility as a logarithmic, concave function of the user's signal-to-interference-plus-noise ratio (SIR) [10], [11], i.e.,

$$u_k = \zeta_k \log(1 + \gamma_k), \qquad (4)$$

where γ_k is the SIR for user k and ζ_k is a constant that is, in general, user-dependent. This utility function is proportional to the Shannon capacity for the user treating all interference as white Gaussian noise. In addition, a pricing function is introduced to prevent the users from always transmitting at full power. In many cases, the pricing function is assumed to be linear in the user's transmit power. Hence, the net utility for user k is given by

$$\tilde{u}_k = \zeta_k \log(1 + \gamma_k) - c_k p_k, \qquad (5)$$

where c_k is the pricing factor for user k.

The authors in [12] define the utility function of a user to be an S-shaped (sigmoidal) function of the user's SIR. In this case, the net utility is defined as the difference between the user's utility function and a (linear) cost function, i.e.,

$$\tilde{u}_k = u_k - c_k p_k, \qquad (6)$$

where, c_k is again the pricing factor and u_k is assumed to be a sigmoidal function of γ_k.

In [13], the authors define a cost function (instead of a utility function) and consider a game in which each user chooses its

[FIG1] The matrix-form representation of the Prisoner's Dilemma game.

		Prisoner 2	
		C	NC
Prisoner 1	C	(−1,−1)	(1,−2)
	NC	(−2,1)	(0,0)

transmit power to minimize its own cost. The cost function for user k is defined as

$$J_k = b_k p_k + c_k \left(\gamma_k^{tar} - \gamma_k \right)^2, \qquad (7)$$

where b_k and c_k are nonnegative constants and γ_k^{tar} is the target SIR for user k. Note that this cost function is convex and nonnegative. Therefore, it has a nonnegative minimum.

When energy efficiency is the main concern, a good choice for the utility function is one that measures the number of bits that can be transmitted per joule of energy consumed. It is clear that a higher SIR level at the output of the receiver will result in a lower bit error rate and hence higher throughput. However, achieving a high SIR level often requires the user terminal to transmit at a high power, which in turn results in low battery life. This tradeoff can be captured by defining the utility function of a user as the ratio of its throughput to its transmit power, i.e.,

$$u_k = \frac{T_k}{p_k}. \qquad (8)$$

Throughput here is the net number of information bits that are transmitted without error per unit time (this sometimes is referred to as goodput). It can be expressed as

$$T_k = R_k f(\gamma_k), \qquad (9)$$

where R_k and γ_k are the transmission rate and the SIR for the kth user, respectively, and $f(\gamma_k)$ is the efficiency function, which represents the packet success rate (PSR). The assumption here is that if a packet has one or more bit errors, it will be retransmitted. This utility function, which has units of bits/joule, represents the total number of reliable bits that are delivered to the destination per joule of energy consumed. It captures very well the tradeoff between throughput and battery life and is particularly suitable for applications where energy efficiency is more important than achieving a high throughput. The utility function in (8) was introduced in [14] and [15] and has been used by others in scenarios in which energy efficiency is the main concern (see for example, [16]–[18]). Obviously, $f(\gamma)$ depends on the details of the data transmission such as modulation, coding, and packet size. However, in most practical cases, $f(\gamma)$ is increasing and S-shaped (sigmoidal) with $f(\infty) = 1$. It is also required for $f(\gamma)$ to be equal to zero when $\gamma = 0$ to make sure that the utility function in (8) does not become infinity when $p_k = 0$ (see [18] for details). Combining (8) with (9), the utility function of the kth user is given by

$$u_k = R_k \frac{f(\gamma_k)}{p_k}. \qquad (10)$$

Using a sigmoidal efficiency function, the shape of the utility function in (10) is shown in Figure 2 as a function of the user's transmit power keeping other users' transmit powers fixed. The utility function in (10) can also be used for coded systems by modifying the efficiency function, $f(\gamma)$, to represent the PSR for the coded system and also scaling the transmission rate appropriately to count only the information bits in a packet.

> POWER CONTROL IS USED FOR INTERFERENCE MANAGEMENT AND RESOURCE ALLOCATION IN WIRELESS NETWORKS, ESPECIALLY CDMA NETWORKS.

POWER CONTROL GAMES

Power control is used for interference management and resource allocation in wireless networks, especially CDMA networks. In the uplink (from the mobile terminal to the base station), the purpose of power control is for each user to transmit just enough power to achieve the required QoS without causing excessive interference in the network. Power control for CDMA systems has been studied extensively over the past decade (see for example [19]–[25]). The conventional approach has been to model power control as a constrained optimization problem, where the total transmit power is minimized under the constraint that the users' QoS requirements are satisfied. The QoS requirement for a user is usually expressed as a lower bound on the user's output SIR. In [20], the authors propose a distributed algorithm for reaching the optimum power levels. In [21], a unified framework for distributed power control in cellular networks is proposed. Alternatively, the transmit powers of the users can be chosen in such a way as to maximize the spectral efficiency (in b/s/Hz). In this approach, the optimal power control strategy is essentially a water-filling scheme (see [23]). In [25], the authors use tools from geometric programming to study power control.

Recently, game theory has been used to study power control in CDMA systems (see, for example, [10]–[12], [14]–[17], and [26]–[30]). Each user seeks to choose its transmit power
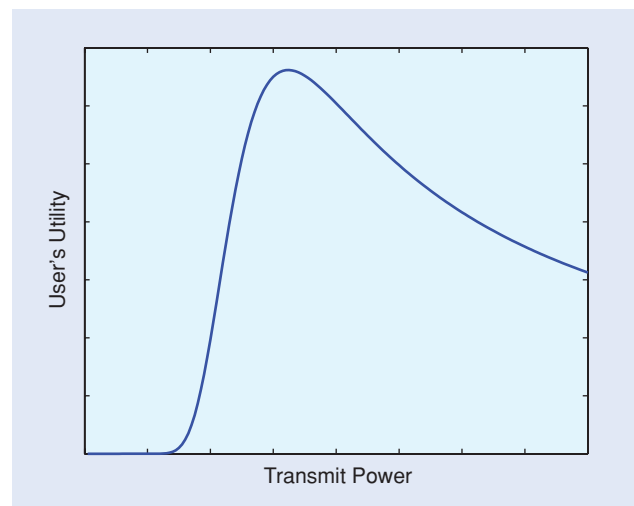
[FIG2] User's utility as a function of transmit power for fixed interference.

in order to maximize its utility. As mentioned previously, the choice of the utility has a great impact on the nature of the game and the resulting NE. In [10] and [11], the utility function in (5) is chosen for the users, and the corresponding NE solution is derived. In [14] and [15], the authors use the utility function in (8) and show that the resulting NE is SIR-balanced (i.e., all users have the same output SIR). The analysis is extended in [17] by introducing pricing to improve the efficiency of NE. Joint network- centric and user-centric power control is discussed in [28]. In [29], the utility function is assumed to be proportional to the user's throughput, and a pricing function based on the normalized received power of the user is proposed. S-modular power control games are studied in [30]. In particular, the conditions for existence and uniqueness of NE for an S-modular game are discussed, and convergence of best-response algorithms is studied.

> OUR FOCUS THROUGHOUT IS ON NONCOOPERATIVE (DISTRIBUTED) GAMES, WHERE EACH USER SEEKS TO MAXIMIZE ITS OWN UTILITY.

In the following sections, we present a family of noncooperative power control games for resource allocation in a variety of CDMA networks with emphasis on energy efficiency. In all these games, the utility function measures the number of reliable bits that are transmitted per joule of energy consumed, similar to the utility function given in (10). We discuss power control games in which, in addition to choosing their transmit powers and depending on the scenario, the users can choose their uplink receivers, MIMO processing algorithms, modulation schemes, transmission rates, and carrier allocation strategies. We also discuss the cases where the users seek to maximize their energy efficiency while satisfying their delay QoS constraints.

Our focus throughout this article is on noncooperative (distributed) games, where each user seeks to maximize its own utility. An alternative approach would be to maximize the sum of the users' utilities. The solution to this problem would correspond to a point on the Parteo-optimal frontier. However, obtaining a closed-form solution for such an optimization problem is usually very difficult. In addition, the solution typically requires coordination among users and, hence, is not scalable.

ENERGY-EFFICIENT POWER CONTROL

In [14] and [15], a noncooperative game is proposed in which each user chooses its transmit power in such a way as to maximize its own energy efficiency (measured in bits/joule). To be more specific, let $\mathcal{G} = [\mathcal{K}, \{\mathcal{A}_k\}, \{u_k\}]$ denote a noncooperative game where $\mathcal{K} = \{1, \ldots, K\}$, and $\mathcal{A}_k = [0, P_{max}]$ is the strategy set for the kth user. Here, P_{max} is the maximum allowed power for transmission. For this game, the best-response strategy for user k is given by the solution of the following maximization problem:

$$\max_{p_k} u_k = \max_{p_k} R_k \frac{f(\gamma_k)}{p_k} \quad \text{for} \quad k = 1, \ldots, K. \quad (11)$$

Recall that with random spreading, the output SIR for a matched filter (MF) receiver is given by

$$\gamma_k = \frac{p_k h_k}{\sigma^2 + \frac{1}{N} \sum_{j \neq k} p_j h_j}. \quad (12)$$

Assuming an MF receiver, it is shown in [15] that the user's utility is maximized when the user transmits at a power level that achieves an SIR equal to γ^* at the output of the receiver, where γ^* is the unique (positive) solution of

$$f(\gamma) = \gamma \, f'(\gamma) . \quad (13)$$

It should be noted that, based on (13), γ^* depends only on the physical-layer characteristics of the communication such as modulation, coding, and packet size. If γ^* is not feasible for a user, the user's utility is maximized when the user transmits at the maximum power. Furthermore, it is shown in [14] and [17] that this game has a unique NE and the equilibrium is SIR-balanced, i.e, all users have the same SIR. The existence of an NE is due to the quasiconcavity of the utility as a function of the user's transmit power. (The function u defined on a convex set $\mathcal{S}$ is quasiconcave if every superlevel set of u is convex, i.e., $\{x \in \mathcal{S} | u(x) \geq a\}$ is convex for every value of a. In other words, a function is quasiconcave if there exists a point below which the function is nondecreasing and above which the function is nonincreasing.) The uniqueness of the equilibrium is because of the uniqueness of γ^* and the one-to-one correspondence between the users' output SIRs and transmit powers.

The analysis is further extended in [17] to show that this SIR-balancing NE solution is not Pareto-optimal. In particular, it is shown that if all the users reduce their transmit powers at the same time, the utility will improve for every user. Based on this observation, the authors introduce a linear pricing function and define the net utility of a user as

$$\tilde{u}_k = R_k \frac{f(\gamma_k)}{p_k} - c_k p_k \quad \text{for} \quad k = 1, \ldots, K, \quad (14)$$

where c_k is the pricing factor. This utility function encourages users to transmit at a lower power level, which causes less interference for other users. A new game is proposed in which users maximize their net utilities given in (14). It is shown in [17] that the NE for this game Pareto-dominates the SIR-balancing solution.

JOINT POWER CONTROL AND RECEIVER DESIGN

The cross-layer problem of joint power control and receiver design is studied in [18]. It is shown that for all linear receivers, the noncooperative power control game in which each user maximizes its own utility (energy efficiency) has a unique NE.

The equilibrium is again SIR-balanced. The target SIR is the solution of (13) and is independent of the receiver type. The results are extended to multiantenna systems as well. Using this noncooperative game-theoretic framework, the gains in energy efficiency and network capacity due to sophisticated temporal and spatial signal processing (i.e., multiuser detection and multiantenna processing) are quantified. In particular, using a large-system analysis similar to that presented in [31], it can be shown that, for the MF, the decorrelator (DE) and the linear minimum-mean-square-error (MMSE) receiver, user k's utility at NE is given by

$$u_k = \frac{R_k f(\gamma^*)\bar{h}_k}{\gamma^*\sigma^2}\bar{\Gamma}, \tag{15}$$

where $\bar{\Gamma}$ depends on the receiver:

$$\bar{\Gamma}^{MF} = 1 - \bar{\alpha}\gamma^* \qquad \text{for} \quad \bar{\alpha} < \frac{1}{\gamma^*}, \tag{16}$$

$$\bar{\Gamma}^{DE} = 1 - \alpha \qquad \text{for} \quad \alpha < 1, \tag{17}$$

$$\text{and} \quad \bar{\Gamma}^{MMSE} = 1 - \bar{\alpha}\frac{\gamma^*}{1+\gamma^*} \quad \text{for} \quad \bar{\alpha} < 1 + \frac{1}{\gamma^*}, \tag{18}$$

with $\bar{\alpha} = \frac{\alpha}{m}$ and $\bar{h}_k = \sum_{l=1}^{m} h_{kl}$. Here, α is the system load, which is defined as the ratio of the number of users to the processing gain (i.e., number of users per degree of freedom), m is the number of received antennas, and h_{kl} is the channel gain from the transmit antenna of the kth user to the lth receive antenna. σ^2 is the noise power, which includes other-cell interference.

Figure 3 shows the average utility as a function of the system load for one and two receive antennas for a Rayleigh channel for a user that is 100 m away from the uplink receiver. The figure shows the achieved utilities for the MF, the DE, and the linear MMSE receiver. The dashed lines correspond to single receive antenna case ($m = 1$) and the solid lines represent the case of two receive antennas ($m = 2$). It is seen from the figure that the utility (energy efficiency) improves considerably when the MF is replaced by a multiuser detector. Also, the system capacity (i.e., the maximum number of users that can be accommodated by the system) is larger for the multiuser receivers as compared with the MF. Among all linear receivers, the MMSE detector achieves the highest utility. In addition, significant improvements in user utility and system capacity are observed when two receive antennas are used compared to the single antenna case. The improvement is more significant for the MF and the MMSE receiver as compared with the decorrelating detector. This

> **AMONG ALL LINEAR RECEIVERS, THE MMSE DETECTOR ACHIEVES THE HIGHEST UTILITY.**

is because the MF and the MMSE receiver benefit from both power pooling and interference reduction, whereas the decorrelating detector benefits only from power pooling (see [32]).

Figure 4 shows the average utility of a user as a function of the system load for the MF, the DE, and the MMSE receiver. The solid and dashed lines correspond to the noncooperative and Pareto-optimal solutions, respectively. While the difference between the noncooperative approach and the cooperative solution is significant for the MF, the solutions are identical for the DE and are quite close to each other for the MMSE receiver. The reason is that multiuser detectors do a better job of decoupling the users as compared to the conventional MF.

POWER CONTROL FOR MULTICARRIER CDMA

It is well known that for maximizing the throughput, the optimal power allocation strategy in a single-user system with parallel additive white Gaussian noise (AWGN) channels is waterfilling [33]. The multiuser scenario is more complicated. In [34]–[36], for example, several waterfilling-type approaches have been investigated for multiuser systems to maximize the overall throughput. However, there are many practical situations where enhancing energy efficiency is more important than maximizing throughput. For such applications, it is more important to maximize the number of bits that can be transmitted per joule of energy consumed rather than to maximize the throughput. Focusing on a multicarrier DS-CDMA system
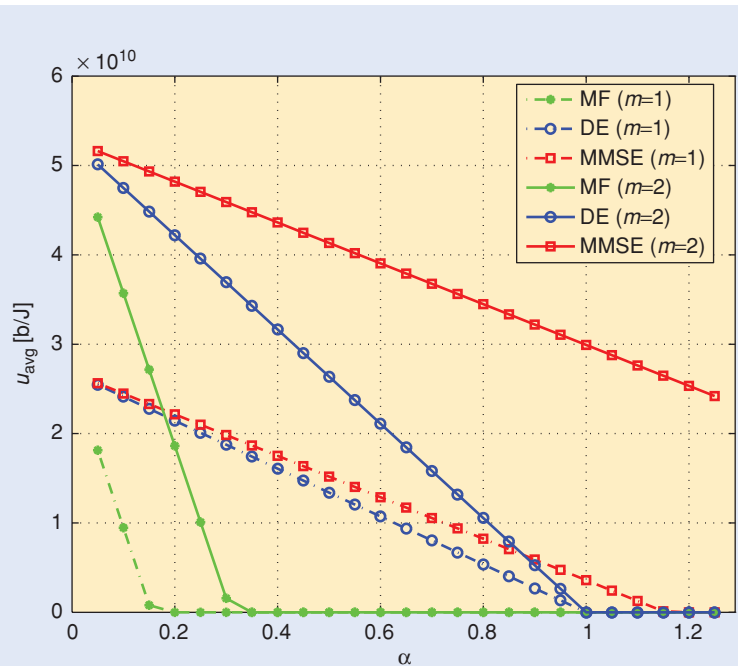
[FIG3] Average utility versus load for the MF, the DE, and the MMSE receiver with one and two receive antennas.

with D carriers, let us consider a noncooperative game in which each user chooses how much power to transmit on each carrier to maximize its overall energy efficiency. Let $\mathcal{G}_D = [\mathcal{K}, \{\mathcal{A}_k^{MC}\}, \{u_k^{MC}\}]$ denote the proposed noncooperative game where $\mathcal{K} = \{1, \cdots, K\}$, and $\mathcal{A}_k^{MC} = [0, P_{\max}]^D$ is the strategy set for the kth user. Here, $P_{\max}$ is the maximum transmit power on each carrier. Each strategy in $\mathcal{A}_k^{MC}$ can be written as $\mathbf{p}_k = [p_{k1}, \cdots, p_{kD}]$, where $p_{k\ell}$ is the transmit power of user k on the ℓth carrier. The utility function for user k is defined as the ratio of the total throughput to the total transmit power for the D carriers, i.e.,

$$u_k^{MC} = \frac{\sum_{\ell=1}^{D} T_{k\ell}}{\sum_{\ell=1}^{D} p_{k\ell}}, \qquad (19)$$

where $T_{k\ell}$ is the throughput achieved by user k over the ℓth carrier and is given by $T_{k\ell} = R_k f(\gamma_{k\ell})$, with $\gamma_{k\ell}$ denoting the received SIR for user k on carrier ℓ. Hence, the utility-maximizing strategy for a user is given by the solution of

$$\max_{\mathbf{p}_k} u_k^{MC} = \max_{p_{k1}, \cdots, p_{kD}} \frac{\sum_{\ell=1}^{D} T_{k\ell}}{\sum_{\ell=1}^{D} p_{k\ell}} \quad \text{for} \quad k = 1, \cdots, K, \quad (20)$$

under the constraint of nonnegative powers (i.e., $p_{k\ell} \geq 0$ for all $k = 1, \cdots, K$ and $\ell = 1, \cdots, D$). The multidimensional nature of users' strategies and nonquasiconcavity of the utility function makes the multicarrier problem much more challenging than the single-carrier case.

It is shown in [37] that, for all linear receivers and with all other users' transmit powers being fixed, user k's utility function, given by (19), is maximized when

$$p_{k\ell} = \begin{cases} p_{kL_k}^* & \text{for} \quad \ell = L_k \\ 0 & \text{for} \quad \ell \neq L_k, \end{cases} \qquad (21)$$

where $L_k = \arg\min_{\ell} p_{k\ell}^*$ with $p_{k\ell}^*$ being the transmit power required by user k to achieve an SIR equal to γ^* on the ℓth carrier, or $P_{\max}$ if γ^* cannot be achieved. Here, γ^* is the again the solution of $f(\gamma) = \gamma \, f'(\gamma)$.

This suggests that the utility for user k is maximized when the user transmits only over its best carrier such that the achieved SIR at the output of the uplink receiver is equal to γ^*. The best carrier is the one that requires the least amount of transmit power to achieve γ^* at the output of the receiver. This solution is different from the waterfilling solution that is obtained when maximizing simply throughput [38]. Depending on the channel gains, the multicarrier power control game may have no equilibrium, a unique equilibrium, or more than one equilibrium (see [37]). Furthermore, with a high probability, at NE, the users are evenly distributed among the carriers. It is also shown that the best-response greedy algorithm in which each user iteratively and distributively maximizes its own utility converges to the NE (when it exists).

Figure 5 compares the approach of joint maximization of utility over all carriers with an approach in which the user's utility is maximized over each carrier independently. A significant improvement in the utility is achieved when joint maximization over all carriers is used. This is because in the joint optimization approach, each user transmits only on its best carrier. This way, the users perform a distributed interference avoidance mechanism, which results in a higher overall utility.

JOINT POWER AND RATE CONTROL WITH DELAY QoS CONSTRAINTS

Tradeoffs between energy efficiency and delay have recently gained considerable attention. The tradeoffs in the single-user case are studied in [39]–[42]. The multiuser problem in turn is considered in [43] and [44]. In [43], the authors present a centralized scheduling scheme to transmit the arriving packets within a specific time interval such that the total energy consumed is minimized, whereas in [44], a distributed ALOHA-type scheme is proposed for achieving energy-delay tradeoffs. The energy-delay tradeoff for CDMA
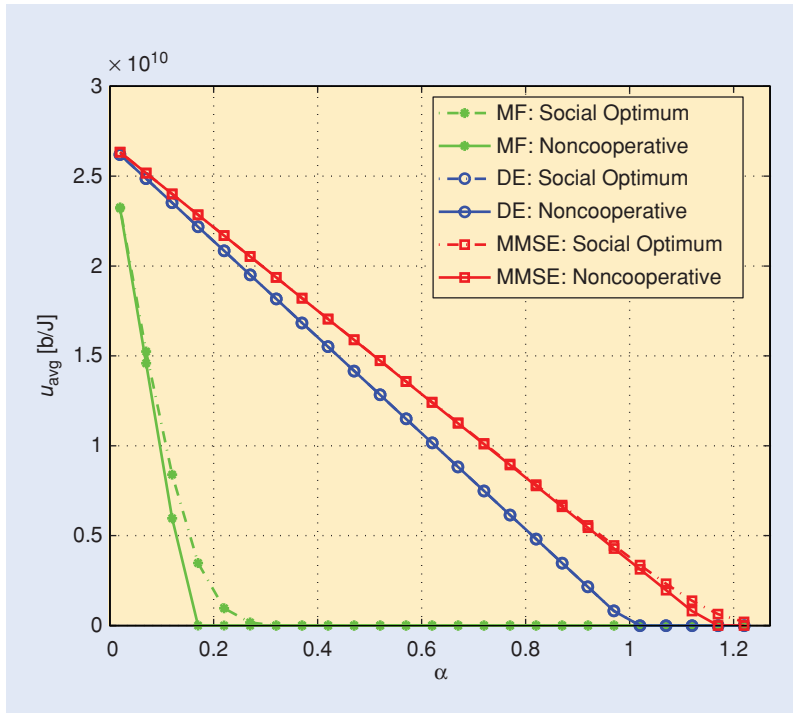
[FIG4] Average utility versus load for the MF, the DE, and the MMSE receiver (single receive antenna).

networks is analyzed in [45] and [46] using a game-theoretic framework.

Consider a noncooperative game in which each user seeks to choose its transmit power and transmission rate to maximize its energy efficiency while satisfying its delay QoS requirements. The packet arrival at the user's terminal is assumed to have a Poisson distribution with an average rate of λ_k. The user transmits the arriving packets, which consist of M bits, at a rate R_k (b/s) and with a transmit power equal to p_k Watts. The user keeps retransmitting a packet until the packet is received error-free. The incoming packets are assumed to be stored in a queue and transmitted in a first-in-first-out (FIFO) fashion. The combination of user k's queue and wireless link can be modeled as an M/G/1 queue. Now, let W_k represent the total packet delay for user k including queuing and transmission delays. We require the average delay for user k's packets to be less than or equal to D_k. Hence, the proposed joint power and rate control can be expressed as the following constrained maximization:

$$\max_{p_k, R_k} u_k \quad \text{s.t.} \quad \bar{W}_k \leq D_k. \tag{22}$$

It is shown in [46] that the delay constraint of a user translates into a lower bound for the user's output SIR. Furthermore, any combination of transmit power p_k and transmission rate R_k such that $\gamma_k = \gamma^*$ and $R_k \geq \Omega_k^*$ maximizes user k's utility. Ω_k^* here corresponds to the rate at which user k meets its delay constraint with equality when $\gamma_k = \gamma^*$ and is given by

$$\Omega_k^* = \left(\frac{M}{D_k}\right) \frac{1 + D_k\lambda_k + \sqrt{1 + D_k^2\lambda_k^2 + 2(1 - f(\gamma^*))D_k\lambda_k}}{2f(\gamma^*)}. \tag{23}$$

This means that the joint power and rate control game has infinitely many Nash equilibria. However, the equilibrium corresponding to $R_k = \Omega_k^*$ with $\gamma_k = \gamma^*$ is the Pareto-dominant equilibrium. Using this framework, the loss in energy efficiency and network capacity due to the presence of delay-sensitive users can be quantified. In particular, the QoS constraints of a user can be translated into a size for the user that is an indication of the amount of resources consumed by the user. For a MF receiver, at Pareto-dominant NE, the size of user k is given by

$$\Phi_k^* = \frac{1}{1 + \frac{B}{\Omega_k^*\gamma^*}}, \tag{24}$$

where B is the system bandwidth. The necessary and sufficient condition for this equilibrium to be feasible is given by
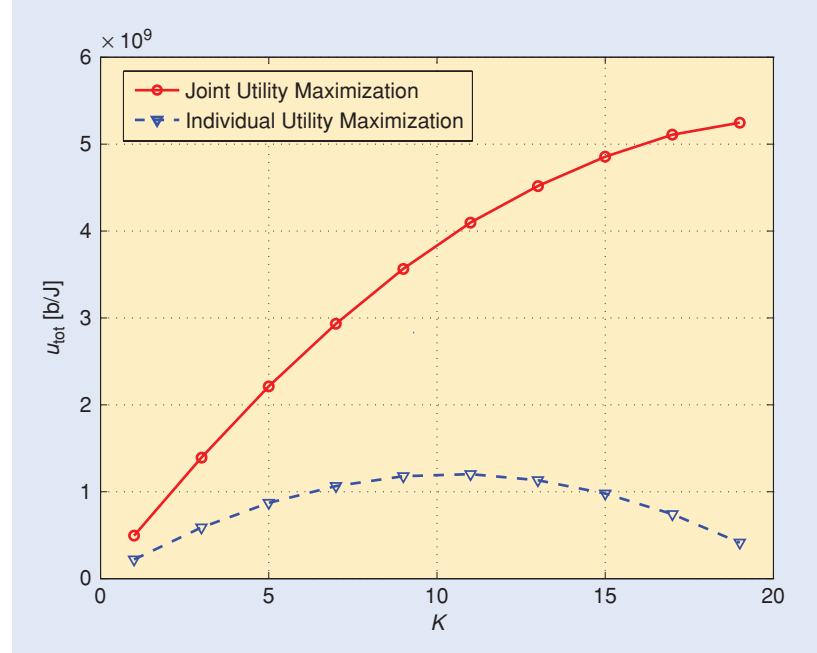
[FIG5] Total utility versus number of users, K, for the two-carrier case with processing gain equal to 128.

$$\sum_{k=1}^{K} \Phi_k^* < 1. \tag{25}$$

Furthermore, the utility of user k at the Pareto-dominant NE is given by (see [46])

$$u_k = \left(\frac{Bh_k f(\gamma^*)}{\sigma^2\gamma^*}\right) \frac{1 - \sum_{i=1}^{K} \Phi_i^*}{1 - \Phi_k^*}, \tag{26}$$

where, as before, σ^2 is the noise power (including other-cell interference) and h_ℓ is the channel gain. Equations (24)–(26) allow us to quantify the tradeoffs among delay, energy efficiency, throughput and network capacity for the multiuser, competitive setting under consideration.

Figure 6 shows the user size, network capacity, transmission rate, and total goodput (i.e., reliable throughput) as a function of normalized delay for different source rates. The delay is normalized by the inverse of the system bandwidth. The network capacity refers to the maximum number of users that can be admitted into the network assuming that all the users have the same QoS requirements (i.e., the same size). The transmission rate and goodput are normalized by the system bandwidth. The total goodput is obtained by multiplying the source rate by the total number of users. As the QoS requirements become more stringent (i.e., a higher source rate and/or a smaller delay), the size of the user increases, which means more network resources are required to accommodate the user. This results in a reduction in the network capacity. It is also observed from the figure that when the delay constraint is loose, the total goodput is almost

independent of the source rate. This is because a lower source rate is compensated by the fact that more users can be admitted into the network. On the other hand, when the delay constraint is tight, the total goodput is higher for larger source rates.
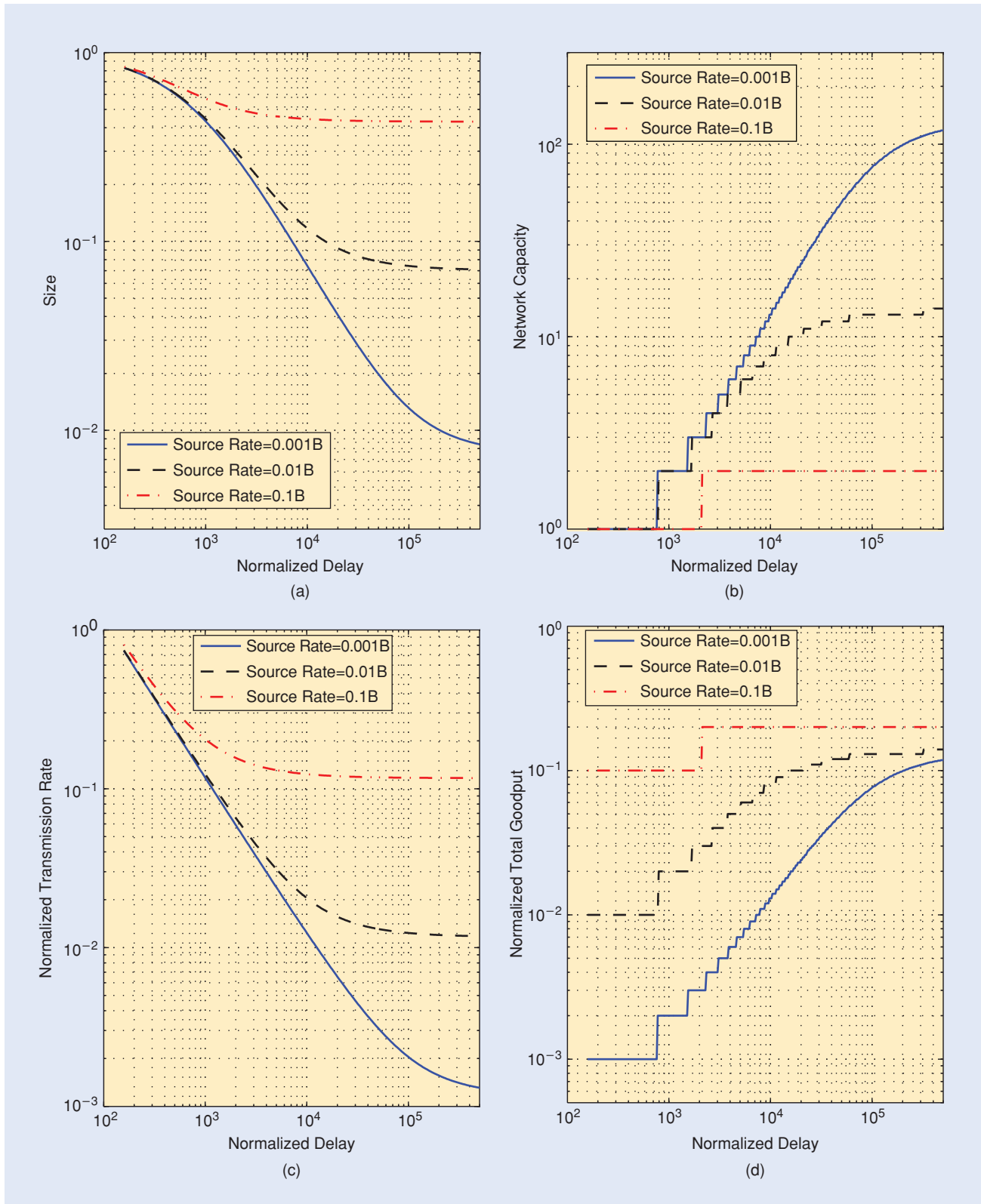
[FIG6] User size, network capacity, normalized transmission rate, and normalized total goodput as a function of normalized delay for different source rates (*B* = 5 MHz).

The effect of modulation on energy efficiency has also been studied in [47] in a similar manner. In particular, a noncooperative game is proposed in which each user can choose its modulation level (e.g., 16-QAM or 64-QAM) as well as its transmit power and transmission rate. It is shown that, in terms of energy efficiency, it is best for a user to choose the lowest modulation level that can satisfy the user's delay QoS constraints. This strategy is again different from the one obtained when maximizing simply throughput. Incorporating the choice of the modulation order into utility maximization allows us to trade off energy efficiency with spectral efficiency. For the same bandwidth and symbol rate, as a user switches to a higher-order modulation, the spectral efficiency for the user improves but its energy efficiency degrades (see [47] for more details).

> **THE GAME-THEORETIC FRAMEWORK ARTICLE IS SUITABLE FOR STUDYING RESOURCE ALLOCATION IN WIRELESS AD HOC NETWORKS AND WLANS.**

DISCUSSIONS AND CONCLUSIONS

The objective of this article has been to provide an overview of game-theoretic approaches to energy-efficient resource allocation in wireless data networks. We have shown that game theory can be used as a unifying framework for studying radio resource management in wireless CDMA networks. Focusing on multiple-access networks, we have presented a number of noncooperative power control games in which each user seeks to maximize its own utility while satisfying its QoS requirements. The utility function considered here measures the number of reliable bits transmitted per joule of energy consumed and is particularly useful for energy-constrained networks. The actions open to each user in trying to maximize its utility have been at least the choice of transmit power and, depending on the situation, each user may also be able to choose its transmission rate, modulation scheme, uplink receiver type, multiantenna processing algorithm, or carrier allocation strategy. The best-response strategies and the NE solutions for these power control games have been presented. Using this game-theoretic approach, the effects of power control, rate control, modulation, temporal and spatial signal processing, carrier allocation strategy, and delay QoS constraints on energy efficiency and network capacity have been studied and quantified in a competitive multiuser setting. In addition, it is seen that in many cases, energy-efficient resource allocation algorithms are not spectrally efficient. Hence, there is a clear tradeoff between maximizing energy efficiency and maximizing spectral efficiency.

The game-theoretic framework discussed in the article is also very suitable for studying resource allocation in wireless ad hoc networks and wireless local area networks (WLANs). Noncooperative games are very useful for analyzing ad hoc networks due to the decentralized nature of the communication (see [1]). Energy efficiency is also very important in wireless ad hoc networks. However, the main challenge is to define an appropriate utility function that captures the multihop nature of the communication in ad hoc networks but at same time is tractable analytically. In WLANs, users communicate to the access point through random access schemes. A user must first compete with other users in the network to capture the channel. Once the channel is captured, the user will have the entire bandwidth to itself for packet transmission. If a user is too aggressive in its attempts for capturing the channel, it will cause many collisions, which will degrade the user's throughput. On the other hand, if the user is too passive, it will not have access to the channel very often and, hence, its throughput degrades. Game theory is an effective tool for modeling the users' interactions in such a system (see, for example, [48] and [49]). Other possible areas for further research are more extensive performance comparison between noncooperative and cooperative resource allocation schemes, and inclusion of channel variation into the utility maximization.

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