ABSTRACT
A game-theoretic model is proposed to study the cross-layer problem of joint power and rate control with quality of service (QoS) constraints in multiple-access networks. In the proposed game, each user seeks to choose its transmit power and rate in a distributed manner in order to maximize its own utility and at the same time satisfy its QoS requirements. The user’s QoS constraints are specified in terms of the average source rate and average delay. The utility function considered here measures energy efficiency and the delay includes both transmission and queueing delays. The Nash equilibrium solution for the proposed non-cooperative game is derived and a closed-form expression for the utility is shown. It is shown that the QoS requirements of a user translate into a “size” for the user which is an indication of the amount of network resources consumed by the user. Using this framework, the tradeoffs among throughput, delay, network capacity and energy efficiency are also studied.

Categories and Subject Descriptors
C.2.1 [Computer-Communication Networks]: Network Architecture and Design—wireless communication, distributed networks

General Terms
Theory, performance

Keywords
Energy efficiency, delay, quality-of-service, cross-layer design, game theory, Nash equilibrium, power and rate control

1. INTRODUCTION
Future wireless networks are expected to support a variety of services with diverse quality of service (QoS) requirements. Because of the hostile characteristics of wireless channels and scarcity of radio resources such as energy and bandwidth, efficient resource allocation schemes are necessary for design of high-performance wireless networks. The objective is to use the radio resources as efficiently as possible and at the same time satisfy the QoS requirements of the users which can be expressed in terms of constraints on rate, delay or fidelity.

Since in most practical scenarios, the users’ terminals are battery-powered, energy efficient resource allocation is crucial to prolonging the battery life of the terminals. In this work, we study the cross-layer problem of QoS-constrained joint power and rate control in wireless networks using a game-theoretic framework. We consider a multiple-access network and propose a non-cooperative game in which each user seeks to choose its transmit power and rate in such a way as to maximize its energy-efficiency (measured in bits per joule) and at the same time satisfy its QoS requirements. The QoS constraints are in terms of the average source rate and average total delay (transmission plus queueing delay). We derive the Nash equilibrium solution for the proposed game and use this framework to study tradeoffs among throughput, delay, network capacity and energy efficiency. Network capacity here refers to the maximum number of users that can be accommodated by the network.

Joint power and rate control with QoS constraints have been studied extensively for multiple-access networks (see for example [1] and [2]). In [1], the authors study joint power and rate control under bit-error rate (BER) and average delay constraints. [2] considers the problem of globally optimizing the transmit power and rate to maximize throughput of non-real-time users and protect the QoS of real-time users. Neither work takes into account energy-efficiency. Recently tradeoffs between energy efficiency and delay have gained more attention. The tradeoffs in the single-user case are studied in [3] and [4]. The multiuser problem in turn is considered in [5] and [6]. In [5], 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 [6], a distributed ALOHA-type scheme is proposed for achieving energy-delay tradeoffs. Joint power and rate control for maximizing goodput in delay-constrained networks is studied in [7].
This work is the first study of QoS-constrained power and rate control in multiple-access networks using a game-theoretic framework. In our proposed game-theoretic model, users choose their transmit powers and rates in a competitive and distributed manner in order to maximize their energy efficiency and at the same time satisfy their QoS requirements. Using this framework, we also analyze the tradeoffs among throughput, delay, network capacity and energy efficiency. Even though a centralized approach is possible due to presence of an access point (AP), a distributed mechanism is more attractive due to its scalability and low complexity. It should be noted that game-theoretic approaches to power control have previously been studied in various work (see for example [10, 17]). However, [10, 16] do not take into account the effect of delay, and [17] only considers transmission delay and does not perform any rate control.

The remainder of this paper is organized as follows. In Section 2 we describe the system model. The proposed joint power and rate control game is discussed in Section 3 and its Nash equilibrium solution is derived in Section 4. We then describe an admission control scheme in Section 5. Tradeoffs among throughput, delay, network capacity and energy efficiency are studied in Section 6 using numerical results. Finally, we give conclusions in Section 7.

2. SYSTEM MODEL

We consider a direct-sequence code-division multiple-access (DS-CDMA) network and propose a non-cooperative (distributed) game in which each user seeks to choose its transmit power and rate to maximize its energy efficiency (measured in bits per joule) while satisfying its QoS requirements. We specify the QoS constraints of user $k$ by $(r_k, D_k)$ where $r_k$ is the average source rate and $D_k$ is the upper bound on average delay. The delay includes both queueing and transmission delays. The incoming traffic is assumed to have a Poisson distribution with parameter $\lambda_k$ which represents the average packet arrival rate with each packet consisting of $M$ bits. The source rate (in bit per second) is hence given by $r_k = M \lambda_k$.

The user transmits the arriving packets at a rate $R_k$ (bps) and with a transmit power equal to $p_k$ Watts. We consider an automatic-repeat-request (ARQ) mechanism in which the user keeps retransmitting a packet until the packet is received at the access point without any errors. The incoming packets are assumed to be stored in a queue and transmitted in a first-in-first-out (FIFO) fashion. The packet transmission time for user $k$ is defined as

$$\tau_k = \frac{M}{R_k} + \epsilon_k \simeq \frac{M}{R_k},$$

where $\epsilon_k$ represents the time taken for the user to receive an ACK/NACK from the access point. We assume $\epsilon_k$ is negligible compared to $\frac{M}{R_k}$. The packet success probability (per transmission) is represented by $f(\gamma_k)$ where $\gamma_k$ is the received signal-to-interference-plus-noise ratio (SIR) for user $k$. The retransmissions are assumed to be independent. The packet success rate, $f(\gamma)$, is assumed to be increasing and S-shaped (sigmoidal) with $f(0) = 0$ and $f(\infty) = 1$. This is a valid assumption for many practical scenarios as long as the packet size is reasonably large (e.g., $M = 100$ bits).

We can represent the combination of user $k$‘s queue and wireless link as an M/G/1 queue, as shown in Figure 1.

Figure 1: System model based on an M/G/1 queue.

where the traffic is Poisson with parameter $\lambda_k$ (in packets per second) and the service time, $S_k$, has the following probability mass function (PMF):

$$\Pr\{S_k = m\tau_k\} = f(\gamma_k)(1 - f(\gamma_k))^{m-1} \text{ for } m = 1, 2, \cdots$$

As a result, the service rate, $\mu_k$, is given by

$$\mu_k = \frac{1}{E[S_k]} = \frac{f(\gamma_k)}{\tau_k},$$

and the load factor $\rho_k = \frac{\mu_k}{\lambda_k} = \frac{\lambda_k}{\tau_k}$. To keep the queue of user $k$ stable, we must have $\rho_k < 1$ or $f(\gamma_k) > \lambda_k \tau_k$. Now, let $W_k$ be a random variable representing the total packet delay for user $k$. This delay includes the time the packet spends in the queue as well as the service time. It is known that for an M/G/1 queue the average wait time (including the queueing and service time) is given by

$$W_k = \frac{\bar{L}_k}{\lambda_k},$$

where $\bar{L}_k = \rho_k + \frac{\rho_k^2 + \lambda_k^2 \sigma_k^2}{2(1 - \rho_k)}$ with $\sigma_k^2$ being the variance of the service time [18]. Therefore, the average packet delay for user $k$ is given by

$$W_k = \tau_k \left(\frac{1 - \lambda_k \tau_k}{f(\gamma_k) - \lambda_k \tau_k}\right) \text{ with } f(\gamma_k) > \lambda_k \tau_k.$$

We require the average delay for user $k$’s packets to be less than or equal to $D_k$. This translates to

$$W_k \leq D_k$$

or

$$f(\gamma_k) \geq \lambda_k \tau_k + \frac{\tau_k}{D_k} - \frac{\lambda_k \tau_k^2}{2D_k}.$$  

However, since $0 \leq f(\gamma_k) < 1$, $\frac{\tau_k}{D_k}$ is possible only if

$$0 \leq \lambda_k \tau_k + \frac{\tau_k}{D_k} - \frac{\lambda_k \tau_k^2}{2D_k} < 1.$$  

This means that $\lambda_k$ and $D_k$ are feasible only if they satisfy $\frac{\tau_k}{D_k}$. Note that the upper bound on the average delay

\[\text{Note that } f(\gamma) = 1 \text{ requires an infinite SIR which is not practical.}\]
where \( \hat{\gamma}_k \) is the channel gain for user \( k \) and \( \sigma^2 \) is the noise power in the bandwidth \( B \).

Let us first look at the maximization in (14) without any constraints, i.e.,

\[
\max_{p_k, R_k} u_k \equiv \max_{p_k, R_k} \frac{f(\hat{\gamma}_k)}{p_k}.
\]

**Theorem 1.** The unconstrained utility maximization in (14) has an infinite number of solutions. More specifically, any combination of \( p_k \) and \( R_k \) that achieves an output SIR equal to \( \gamma^\ast \), the solution to \( f(\gamma) = \gamma f'(\gamma) \), maximizes \( u_k \).

**Proof.** Let \( \tilde{p}_k \) and \( \tilde{R}_k \) be any power-rate combination such that

\[
\left( \frac{B}{\tilde{R}_k} \right) \frac{\tilde{p}_k h_k}{\sigma^2 + \sum_{j \neq k} p_j h_j} = \tilde{\gamma}.
\]

Then, we have

\[
\tilde{u}_k = \tilde{R}_k \frac{f(\tilde{\gamma})}{\tilde{p}_k} = \frac{B h_k}{\tilde{\gamma}} f(\tilde{\gamma}),
\]

where

\[
\hat{h}_k = \frac{h_k}{\sigma^2 + \sum_{j \neq k} p_j h_j}.
\]

This means that when other users’ powers and rates are fixed (i.e., fixed \( h_k \)), user \( k \)’s utility depends only on \( \hat{\gamma}_k \) and is independent of the specific values of \( p_k \) and \( R_k \). In addition, by taking the derivative of \( f(\gamma) / \gamma \) with respect to \( \gamma \) and equating it to zero, it can be shown that \( f(\gamma) / \gamma \) is maximized when \( \gamma = \gamma^\ast \), the (unique) positive solution of \( f(\gamma) = \gamma f'(\gamma) \). Therefore, \( u_k \) is maximized for any combination of \( p_k \) and \( R_k \) for which \( \hat{\gamma}_k = \gamma^\ast \). This means that there are infinitely many solutions for the unconstrained maximization in (14).

The second constraint in (14) can equivalently be expressed as

\[
R_k > \left( \frac{M}{D_k} \right) 1 + D_k \lambda_k + \sqrt{1 + D_k^2 \lambda_k^2}.
\]

Therefore, the maximization in (14) is equivalent to

\[
\max_{p_k, R_k} \left[ \frac{R_k f(\hat{\gamma}_k)}{p_k} \right] \quad \text{s.t.} \quad \hat{\gamma}_k > \gamma_k \quad \text{and} \quad R_k > \left( \frac{M}{D_k} \right) 1 + D_k \lambda_k + \sqrt{1 + D_k^2 \lambda_k^2}.
\]

Let us define

\[
\Omega_k^\ast = \left( \frac{M}{D_k} \right) 1 + D_k \lambda_k + \sqrt{1 + D_k^2 \lambda_k^2}.
\]

Note that for \( R_k = \Omega_k^\ast \), we have \( \eta_k = 1 \) and hence \( \hat{\gamma}_k = \infty \). Also, define \( \Omega_k^\ast \) as the rate for which \( \gamma_k = \gamma^\ast \), i.e.,

\[
\Omega_k^\ast = \left( \frac{M}{D_k} \right) 1 + D_k \lambda_k + \sqrt{1 + D_k^2 \lambda_k^2} + 2(1 + f^\ast) D_k \lambda_k.
\]

where \( f^\ast = f(\gamma^\ast) \). It is easy to show that \( \gamma_k > \gamma^\ast \) for all \( \Omega_k^\ast < R_k < \Omega_k^\ast \). This means that based on (15), user \( k \) has no incentive to transmit at a rate smaller than \( \Omega_k^\ast \). Furthermore, based on Theorem 1, any combination of \( p_k \) and \( R_k \geq \Omega_k^\ast \) that results in an output SIR equal to \( \gamma^\ast \) is a solution to the constrained maximization in (14). Note that when \( R_k = \Omega_k^\ast \) and \( \gamma_k = \gamma^\ast \), we have \( \hat{\gamma}_k = D_k \).
4. NASH EQUILIBRIUM FOR THE PRCG

For a non-cooperative game, a Nash equilibrium is defined as a set of strategies for which no user can unilaterally improve its own utility [29]. We saw in Section 3 that for our proposed non-cooperative game, each user has infinitely many strategies that maximize the user’s utility. In particular, any combination of \( p_k \) and \( R_k \) for which \( \gamma_k = \gamma^* \) and \( R_k \geq \Omega_k \) is a best-response strategy.

**Theorem 2.** If \( \sum_{k=1}^{K} \frac{1}{1 + \frac{1}{R_k}} < 1 \), then the PRCG has at least one Nash equilibrium given by \( (p_k^*, \Omega_k^*) \), for \( k = 1, \ldots, K \), where \( p_k^* = \frac{h_k^2}{\gamma_k^*} \left( 1 + \frac{1}{1 + \frac{1}{R_k^*}} \right) \) and \( \Omega_k^* \) is given by \( \Box \). Furthermore, when there are more than one Nash equilibrium, \( (p_k^*, \Omega_k^*) \) is the Pareto-dominant equilibrium.

**Proof.** If \( \sum_{k=1}^{K} \frac{1}{1 + \frac{1}{R_k}} < 1 \) then \( p_k^* \) is positive and finite. Now, if we let \( \hat{p}_k = p_k^* \) and \( R_k = \Omega_k^* \), then the output SIR for all the users will be equal to \( \gamma^* \) which means every user is using its best-response strategy. Therefore, \( (p_k^*, \Omega_k^*) \) for \( k = 1, \ldots, K \) is a Nash equilibrium.

More generally, if we let \( R_k = \hat{R}_k \geq \Omega_k^* \) and provided that \( \sum_{j=1}^{K} \frac{1}{1 + \frac{1}{R_j^*}} < 1 \), then \( (\hat{p}_k, \hat{R}_k) \) is a Nash equilibrium at Nash equilibrium, the utility of user \( k \) is given by

\[
\begin{align*}
  u_k &= \frac{B \ell f(\gamma^*)}{\sigma^2 \gamma^*} \left( 1 - \sum_{i \neq k} \frac{1}{1 + \frac{1}{R_i}} \right) \left( \frac{1}{1 + \frac{1}{\hat{R}_k \gamma^*}} \right). \\
\end{align*}
\]

Therefore, the Nash equilibrium with the smallest \( \hat{R}_k \) achieves the largest utility. A higher transmission rate for a user requires a larger transmit power by that user to achieve \( \gamma^* \). This not only reduces the user’s utility but also causes more interference for other users in the network and forces them to raise their transmit powers as well which will result in a reduction in their utilities. This means that the Nash equilibrium with \( R_k = \Omega_k^* \) and \( p_k^* \) for \( k = 1, \ldots, K \) is the Pareto-dominant equilibrium. \( \Box \)

Based on the feasibility condition given by Theorem 2, let us define the “size” of user \( k \) as

\[
\Phi_k^* = \frac{1}{1 + \frac{1}{R_k}}.
\]

Then, the feasibility condition of Theorem 2 can be written as

\[
\sum_{k=1}^{K} \Phi_k^* < 1.
\]  

Note that the QoS requirements of user \( k \) (i.e., its source rate \( r_k \) and delay constraint \( D_k \)) uniquely determine \( \Omega_k^* \) through [22], and, in turn, determine the size of the user (i.e., \( \Phi_k^* \)) through [23]. The size of a user is basically an indication of the amount of network resources consumed by that user. A larger source rate or a tighter delay constraint for a user increases the size of the user. The network can accommodate a set of users if and only if their total size is less than 1. In Section 6, we use this framework to study the trade-offs among throughput, delay, network capacity and energy efficiency.

5. ADMISSION CONTROL

In Section 4, we defined the “size” of a user based on its QoS requirements. Before joining the network, each user calculates its size using [23] and announces it to the access point. According to [23], the access point admits those users whose total size is less than 1. While the goal of each user is to maximize its own energy efficiency, a more sophisticated admission control can be performed to maximize the total network utility. In other words, out of the \( K \) users, the access point can choose those users for which the total network utility is the largest, i.e.,

\[
\max_{\ell \subset \{1, \ldots, K\}} \sum_{\ell \in L} u_{\ell} \quad \text{under the constraint that } \sum_{\ell \in L} \Phi_{\ell}^* < 1.
\]

Based on [23], the utility of user \( \ell \) at the Pareto-dominant Nash equilibrium is given by

\[
\begin{align*}
  u_{\ell} &= \frac{B h_{\ell} f(\gamma^*)}{\sigma^2 \gamma^*} \frac{1}{1 - \Phi_{\ell}}.
\end{align*}
\]

As a result, [23] becomes

\[
\begin{align*}
  &\max_{\ell \subset \{1, \ldots, K\}} \left( 1 - \sum_{\ell \in L} \Phi_{\ell}^* \right) \sum_{\ell \in L} \frac{h_{\ell}}{1 - \Phi_{\ell}^*} \quad \text{under the constraint that } \sum_{\ell \in L} \Phi_{\ell}^* < 1.
\end{align*}
\]

In general, obtaining a closed-form solution for [23] is difficult since it depends on the channel gains and sizes of the users. Instead, in order to gain some insight, let us consider the special case in which all users are at the same distance from the access point. We first consider the scenario in which the users have identical QoS requirements (i.e., \( \Phi_1^* = \cdots = \Phi_K^* = \Phi^* \)). If we replace \( \sum_{\ell=1}^{L} h_{\ell} \) by \( LE[h] \), then [23] becomes

\[
\begin{align*}
  &\max_{L} \frac{E[h]}{L - L^2 \Phi^*} \cdot \\
\end{align*}
\]

Therefore, the optimal number of users for maximizing the total utility in the network is \( L = \left\lfloor \frac{1}{\Phi^*} \right\rfloor \) where \( \lfloor x \rfloor \) represents the integer nearest to \( x \).

Now consider another scenario in which there are \( C \) classes of users. The users in class \( c \) are assumed to all have the same QoS requirements and hence the same size, \( \Phi^*(c) \). Since we are assuming that all the users are at the same distance from the access point, they all have the same average channel gain. Now, if the access point admits \( L^{(c)} \) users from class \( c \) then the total utility is given by

\[
\begin{align*}
  u_T &= \frac{B EC[h] f(\gamma^*)}{\sigma^2 \gamma^*} \left( 1 - \sum_{c=1}^{C} L^{(c)} \Phi^*(c) \right) \left( \sum_{c=1}^{C} \frac{L^{(c)}}{1 - \Phi^*(c)} \right) \quad \text{provided that } \sum_{c=1}^{C} L^{(c)} \Phi^*(c) < 1.
\end{align*}
\]

It can be shown that \( u_T \) is maximized when \( L^{(1)} = \left\lfloor \frac{1}{\Phi^*(1)} \right\rfloor \) with \( L^{(c)} = 0 \) for \( c = 2, 3, \ldots, C \). This is because adding a user from class \( 1 \) is always more beneficial in terms of increasing the total utility than adding a user from any other class.
Therefore, in order to maximize the total utility in the network, the access point must admit only users from the class with the smallest size. While this solution maximizes the total network utility, it is not fair. A more sophisticated admission control mechanism can be used to improve the fairness. In the next section, we demonstrate the loss in network energy efficiency if a suboptimal admission control strategy is used.

6. NUMERICAL RESULTS

Let us consider the uplink of a DS-CDMA system with a total bandwidth of 5MHz (i.e., $B = 5$MHz). Each user in the network has a set of QoS requirements expressed as $(r_k, D_k)$ where $r_k$ is the source rate and $D_k$ is the delay requirement (upper bound on the average total delay) for user $k$. As explained in Section 4, the QoS parameters of a user define a “size” for that user, denoted by $\Phi_k^*$ given by (24). Before a user starts transmitting, it must announce its size to the access point. Based on the particular admission policy, the access point decides whether or not to admit the user. For the cases where there are multiple equilibria, we assume that the admitted users agree to choose the transmit powers and rates that correspond to the Pareto-dominant Nash equilibrium. This is an important assumption that requires its own study.

Figure 2 shows the user’s utility as a function of delay for different source rates. The total size of the other users in the network is assumed to be 0.2. The user’s utility is normalized by $B h / \sigma^2$, and the delay is normalized by the inverse of the system bandwidth. As expected, a tighter delay requirement and/or a higher source rate results in a lower utility for the user.

Figure 3 shows the user size, network capacity, transmission rate, and total goodput as a function of normalized delay for different source rates. 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.

Now to study admission control, let us consider a network with three different classes of users/sources:

1. Class $A$ users for which $r^{(A)} = 5$kbps and $D^{(A)} = 10$ms, and hence, $\Phi^{(A)} = 0.0198$.

2. Class $B$ users for which $r^{(B)} = 50$kbps and $D^{(B)} = 50$ms, and hence, $\Phi^{(B)} = 0.0718$.

3. Class $C$ users for which $r^{(C)} = 150$kbps and $D^{(C)} = 1000$ms, and hence, $\Phi^{(C)} = 0.1848$.

![Figure 2: Normalized utility as a function of normalized delay for different source rates ($B = 5$MHz). The combined “size” of other users in the network is equal to 0.2.](image)

![Figure 3: User size, network capacity, normalized transmission rate, and normalized total goodput as a function of normalized delay for different source rates ($B = 5$MHz).](image)
Table 1: Percentage loss in the total network utility for different choices of $L^{(A)}, L^{(B)}$ and $L^{(C)}$.

| $L^{(A)}$ | $L^{(B)}$ | $L^{(C)}$ | Loss in total utility |
|-----------|-----------|-----------|-----------------------|
| 25        | 0         | 0         | –                     |
| 23        | 1         | 0         | 10%                   |
| 20        | 0         | 1         | 30%                   |
| 18        | 1         | 1         | 38%                   |
| 0         | 7         | 0         | 71%                   |
| 0         | 0         | 3         | 87%                   |

For the purpose of illustration, let us assume that there are a large number of users in each class and that they all are at the same distance from the access point (i.e., they all have the same average channel gain). The access point receives requests from the users and has to decide which ones to admit in order to maximize the total utility in the network (see (28)). We know from Section 5 that since users in class $A$ have the smallest size, the total utility is maximized if the access point picks users from class $A$ only with $L^{(A)} = 1/2L^{(A)} = 25$. However, this solution does not take into account fairness issues. Instead, we may be more interested in solutions in which more than one class of users are admitted. Table 1 shows the percentage loss in the total utility for several choices of $L^{(A)}, L^{(B)}$ and $L^{(C)}$.

7. CONCLUSIONS

We have studied the cross-layer problem of joint power and rate control with QoS constraints in wireless networks using a game-theoretic framework. We have proposed a non-cooperative game in which users seek to choose their transmit powers and rates in such a way as to maximize their utilities and at the same time satisfy their QoS requirements. The utility function considered here measures the number of reliable bits transmitted per joule of energy consumed. The QoS requirements for a user consist of the average source rate and the average delay where the delay includes both transmission and queueing delays. We have derived the Nash equilibrium solution for the proposed game and obtained a closed-form solution for the user’s utility at equilibrium. Using this framework, we have studied the tradeoffs among throughput, delay, network capacity and energy efficiency, and have shown that presence of users with stringent QoS requirements results in significant reductions in network capacity and energy efficiency.

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