ARC: An Integrated **A**dmission and **R**ate **C**ontrol Framework for CDMA Data Networks Based on Non-Cooperative Games

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ABSTRACT

The competition among wireless data service providers brings in an option for the customers to switch their providers, due to unsatisfactory service or otherwise. However, the existing resource management algorithms for wireless networks fail to fully capture the far-reaching impact of this *competitiveness*. From this perspective, we propose an integrated *admission and rate control* (ARC) framework for CDMA based wireless data networks. The admission control is at the *session* (macro) level while the rate control is at the link layer *packet* (micro) level. The ARC framework is based on a novel game theoretic formulation which defines non-cooperative games between the service providers and the customers. A user's decision to leave or join a provider is based on a finite set of strategies. A service provider can also construct its game strategy set so as to maximize the utility (revenue) yet attaining its target *churn rate* (the probability of users leaving the network). We show that the pure strategy *Nash equilibrium* can be established for both under-loaded and fully-loaded systems such that the providers have clearly defined admission criteria as outcome from this game. Users are categorized into multiple classes and offered *differentiated services* based on the price they pay and the service degradation they can tolerate. We show that the proposed ARC framework significantly increases the provider's revenue and also successfully offers differentiated QoS to the users.

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Categories and Subject Descriptors

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General Terms

Algorithms, Design, Experimentation, Economics, Human Factors, Theory

Keywords

Wireless Data Networks, Admission Control, Rate Control, CDMA systems, Non-cooperative Games

1. INTRODUCTION

Wireless data service is perceived as the most important revenue generating service in future wireless networks. This fact, together with the *competition* faced by the service providers, is imposing unprecedented challenges to the *resource management* problem in such networks. The two major challenges that the wireless data network designers are facing today include (i) establishing the fundamental relationship between the market competitiveness and network design principles, particularly the resource management schemes; and (ii) devising an efficient resource management framework specifically adapted to wireless data delivery.

Since there are usually multiple wireless carriers (service providers) in every region, customers or users have the freedom to choose their own providers. This brings in a new perspective to the wireless network design. The users' decision of leaving the current service provider and subscribing to another is called *churning*. The impact of churning on a competitive environment with two providers is illustrated in Figure 1. Each provider caters to a subset of the total user pool. It is important for the providers to manage the network resources based on the expectation of the users; otherwise they may churn to a different provider. In the traditional regulated telecommunications industry, the freedom of the users to leave a network provider was very limited. The goal of maximizing the provider's revenue (utility), throughput (or resource utilization) in such a single-provider system was harmonious. However, in a *competitive market*, these two goals may not necessarily lead to the same resource management strategy. How the resource management, which is one of the main interactions between the wireless system (representing the service providers) and the customers, should be adjusted to reflect this fundamental change in the market daynamics, has received very less attention so far.

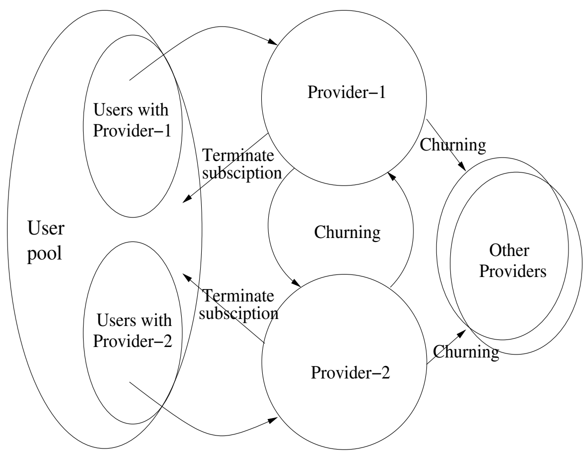

Figure 1: Two-provider Competition Dynamics

Apart from the competition from other providers, the data services themselves are also posing challenges to the network resource management issues. Consider the admission control problem as an example. In a CDMA (Code Division Multiple Access) cellular system only supporting voice services, admitting a new user into the system may result in an *infeasible power assignment* that is very undesirable and should be avoided with extreme care [25]. This judgment comes from the fact that voice is delay sensitive. Infeasible power assignment means immediate dropping of some voice packets because they cannot be buffered. However, wireless data networks are different in nature, due in part to the burstiness of data traffic. Dedicating channels to each data flow is inefficient. Since the wireless links are shared, it is very hard for admission control to make the following judgement: *under what conditions the system is considered fully loaded so that no new request can be accepted.* Infeasible power assignment at the instant of session request, used as the main criterion for admission control in voice networks, does not necessarily mean the system's inability to admit new data session requests. This is because the data flow added by the new session might be buffered for a short time and transmitted later during the "silence" period of other on-going sessions. Therefore, new resource management algorithms, which capture the essential nature of data traffic, are needed to strike a balance between the utilization of the limited wireless bandwidth resource and the customer's satisfaction. While wireless voice networks only need to provide the same quality-of-service (QoS) to all the users (the same BER or bit error rate, the same bandwidth, the same delay, etc.), wireless data networks should be able to provide different QoS to different applications and users. Thus, *differentiated QoS* is a major challenge that the data services bring into the wireless networks.

In this paper, we address the above challenges in a novel way. Our contributions include the following:

- We claim that *in a competitive non-cooperative environment, the ultimate goal of resource management algorithms in network design is maximizing the provider's revenue, instead of maximizing system throughput (or resource utilization) as in a cooperative environment.* By applying this principle to the system design, we propose a novel framework for resource management in wireless data networks based on game theory. We prove this claim by showing significant revenue improvement in our proposed framework over traditional wireless cellular systems.

- We formulate the *admission control* problem at macro (or session) level in wireless data networks as a two-player, nonzero-sum, non-cooperative game between the service provider and the customer requesting for session admission. The non-cooperative nature of the admission control problem due to the market competitiveness is properly modeled in this game with carefully defined payoff functions.

- We show that the proposed formulation of the admission control game formulated achieves Nash Equilibrium for both under-loaded and fully-loaded systems, thus leading to the provider's admission strategy in both cases.

- An admission control scheme has to be used in combination with a proper resource assignment algorithm to make the system feasible and stable. We propose a *rate control* scheme at micro (or packet) level which resides between the link layer and MAC (Media Access Control) multiplexer that buffers the packets from certain flows when the system has more sessions active at a time than the system's power budget may allow.

- With different game parameters, the system is able to provide differentiated QoS to different classes of users, both in terms of session rejection probability and link layer packet delay. This enables the service providers to supply a variety of services to customers with different preferences on QoS, tolerance on service degradation, and financial budget.

The rest of the paper is organized as follows. Section 2 gives a survey of existing work related to the problem we are addressing and the game theoretic approach we are taking. Section 3 describes the proposed framework. Section 4 discusses the admission control game formulation and the equilibrium solution to the game. Section 5 describes the rate control algorithm and the packet blocking probability estimation. Section 6 presents the simulation results to demonstrate the feasibility of the system and the significant improvement in revenue maximization and differentiated QoS provisioning. Section 7 discusses some issues that can be explored in the future and concludes the paper.

2. RELATED WORK

Admission control is one of the most fundamental problems in wireless networks, and has been studied extensively

[1] [7] [9] [15] [25]. Most of the work in CDMA networks focus on avoiding infeasible user(s) getting admitted into the system. "Infeasible user" means if the user is admitted, the power assignment to satisfy the SIR (Signal to Interference Ratio) requirements of all the users in the system becomes infeasible. As a result, some sessions have to be dropped. Another focus on admission control has been to reduce the hand off blocking probability while maximizing the total traffic the system can support, because a low hand off dropping rate is always achieved by reserving resources in the neighboring cells. In [15], an integrated system with both voice and data service is proposed. However, in this approach, data service is just a supplemental service which utilizes the residual bandwidth from the voice service. Such works are suitable for wireless networks mainly supporting voice service, because the system load is always evaluated according to the SIR levels and feasible power assignment. Although they can guarantee the QoS for voice service, they are too conservative for data network where channels (codes for CDMA) can be shared among different users. Moreover, providing feasible power assignment to guarantee SIR for all the users is unnecessary because not all users are transmitting all the time during the session due to the burstiness of data traffic. More importantly, no admission control so far has considered the competitiveness among service providers.

To the best of our knowledge, not much work has been done in jointly addressing the challenges faced by the admission and rate control schemes in wireless data networks. Game theory has been used in a variety of resource management problems in wireless networks. For example, power control problem has been modeled as a non-cooperative game between users competing for the power to reach their SIR requirements [2] [24]. It is shown that such a game can reach Nash equilibrium and produce feasible power assignment. In [16], the application of game theory to media random access problem is discussed. By modeling the users trying to access the same media at the same time as players of the game, it is shown that a random ALOHA with selfish users can also achieve stability for sufficient low attempt rates. However, none of the games formulated in the existing work on power control and access control attempts to capture the competitiveness among the service providers, nor do they aim at maximizing the provider's revenue. In [5], the game concept is used in admission control, but no formal game is formulated nor equilibrium is established.

Cooperative game theory has been used to obtain a Nash bargaining framework to address issues like network efficiency, fairness, revenue maximization and pricing [27]. Repeated non-cooperative games have been used in [17] for market-based modeling to manage network resources, prove existence of a unique Nash equilibrium [18] and its reachability using a de-centralized approach. Game theory has also been used to study the pricing structure of a network. To recover cost, network providers must understand user behavior and demands so as to offer different service plans. In [13], it has been shown how the network can behave as an active player in order to maximize revenue. The network uses its sole discrimination to force users to an operating point that is favorable to the network. Similar approaches using game theory have been used for determining pricing models for the Internet. A pricing model is proposed in [21] for differentiated network services with one seller, one broker and multiple users. The existence of Nash equilibrium with two Internet service providers (ISPs) is studied in [6]. It has been shown that cooperation between two ISPs benefit both the ISPs and the users [8]. The relationship between congestion control and pricing is established in [10], a lot of progress has been made on the Internet pricing. It has been argued in [11] that it is possible to provide differentiated QoS to users using simple pricing schemes obtained from a sequence of games. In [14] an algorithm is proposed for both the network to adjust their price and users to adjust their window (rate) such that an optimal equilibrium is reached, thus maintaining proportional fairness.

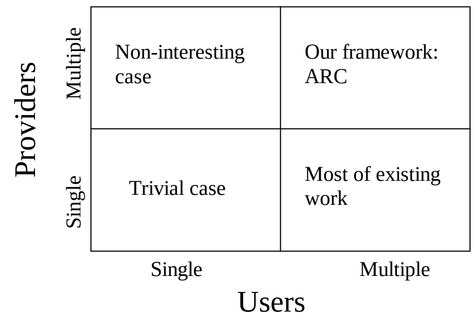

Figure 2: Interactions among service providers and users

Figure 2 categorizes game theoretic formulations into four cases depending on whether the network is dealing with single or multiple providers and users. Most of the existing work based on non-cooperative game theory for resource management in wireless networks do not incorporate the new paradigm of multiple providers or the competition thereof. Our proposed admission and rate control (ARC) framework applies to multiple-user multiple-provider case which we believe has not been addressed in the same manner as proposed in this paper. This case can be easily mapped into the single provider-multiple user case.

3. PROPOSED ARC FRAMEWORK

The architecture of the proposed ARC framework for differentiated wireless services is shown in Figure 3. The CDMA cellular system is connected to the SLA (service level agreement) database of the carrier through the Internet to manage the user policies. It is also connected to the content servers (HTTP or WAP) through the IP backbone. The SLA database carries all the information about the customers and their service plans. The session admission into the system is determined by the admission control algorithm.

In an interference limited multiple access scheme such as CDMA, the admission of a new session into the system has an influence on all the on-going sessions. The admission controller not only has to provide the necessary resources to the new session, but also has to maintain the QoS of the existing ones that was promised to them at the time of admission. There is a "graceful degradation" in the system performance as the number of users in a CDMA system goes up. This means that if additional users are accommodated into the system, then *all* the users in the system will suffer. Thus, in a CDMA system, there is usually a trade-off between the *capacity* (number of users services) and the offered QoS parameters like SIR or the corresponding BER. To summarize,

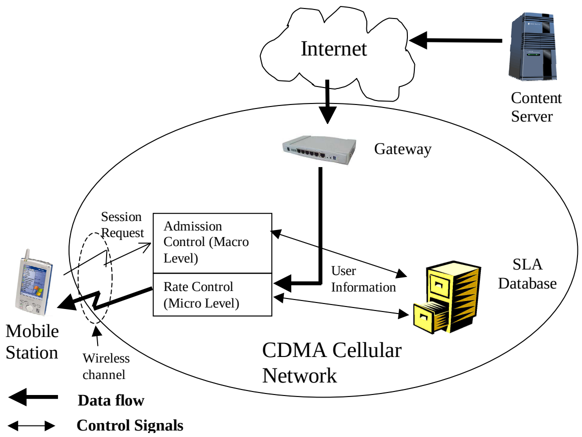

Figure 3: Framework Architecture

the occurrence of a new event, be it a new service request or change in resource usage of an existing session, has some effect which is propagated to all the on-going sessions.

The admission control and rate control algorithms are closely integrated in the ARC framework. Our admission control does not use the traditional criterion directly based on interference measurements and power assignments, hence power assignment to support all the sessions to transmit at the same time with full rate may not be feasible. We allow this to happen intentionally because single flow data traffic is bursty. If we guarantee full rate transmission of all the sessions at the same time, then the system will be underutilized most of the time. However, something has to be done if infeasible power assignment occurs in the system. This is where we use a rate control scheme to reduce the rate of certain sessions. With less power to transmit these lower rate sessions, the feasible power assignment can still be achieved. In our ARC framework, admission control and rate control mechanisms work closely together to maximize the provider's revenue as well as to yield a feasible system.

Our framework provides differentiated services for K classes of users, numbered as classes 1 to K. The smaller the class number, the higher is its priority. A user in a higher priority class pays more premium than a user in a lower priority class, and hence gets higher QoS in terms of lower session blocking probability and packet blocking probability.

4. ADMISSION CONTROL AS A TWO-PLAYER GAME

Let us analyze the competitive wireless service scenario. Assume there are M service providers and N users. At time t, let the number of users subscribing to provider i be denoted as $n(t)_i$, where $1 \leq i \leq M$. Excluding the possibility that a customer subscribes to more than one service provider at the same time, we have $\sum_{i=1}^{M} n(t)_i = N$. The vector $[n(t)_1, n(t)_2, \ldots, n(t)_M]$ changes continuously as the competition dynamics evolves due to the user's churning behavior, as mentioned earlier. Figure. 4 shows one possible status of the system. Note that each user may have M choices for service provider, which makes the possible number of states in the system to be M^N. Modeling this dynamics as one game would make it unmanageably complex. However, if we take a snapshot of the picture in Figure. 4, each user is only associated with one service provider at a time. If we can model this one-to-one relationship between a particular user and his current service provider as a game G_j (for $1 \leq j \leq N$) at any instant, and manage their relationship properly with the game output, then the competitive scenario can be considered as multiple instances of this one-to-one game between two players (provider vs. user).

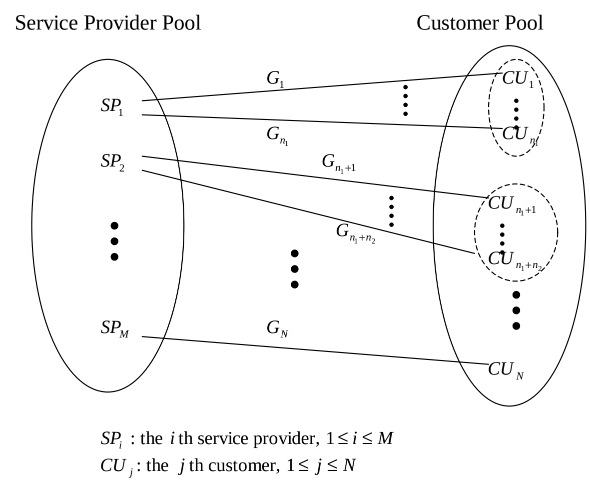

Figure 4: Relationship Between Multiple Providers and Multiple Customers in the Competitive System

We take this approach in the admission control problem formulation since it is one of the main interactions between the wireless data networks and the users. We capture this interaction with a two-player game. In this section, we first introduce the basic concepts in a normal form two-player game. Then we discuss the nature of the game relationship between the network and the user during the admission control process. Finally, the game is formalized and the admission control criteria is derived as the equilibrium solution of the game.

4.1 Preliminaries on Non-cooperative Games

A two-player game is the most basic form of games, but also a powerful tool for solving problems with conflicting goals. In such a game, each player has a set of *strategies*. Two strategies, each coming from the strategy set of a player, form a pair of strategies in the two-player game. Associated with this pair are two *payoffs*, one for each player. Each player makes his decision independently and tries to get the most out of the game on the basis that the other player is not cooperating in anyway. Games can be presented in two forms. Games in *normal form* deal with the situation where decision of each player is made without knowing the decision of the other player. *Extensive form* games deal the situation where at least one player has partial information about other player(s) decision. Since we only use the normal form game in our admission control scheme, we only discuss the games in normal form.

Mathematically, a two-player non-cooperative game consisting of players $\mathcal{P}_1$ and $\mathcal{P}_2$ is defined by two payoff matrices A and B. Assume $\mathcal{P}_1$ has m strategies denoted as $s_1, s_2, \ldots, s_m$ and $\mathcal{P}_2$ has n strategies denoted as $t_1, t_2, \ldots, t_n$. The rows in the payoff matrices represents $\mathcal{P}_1$'s strategy and the columns represents $\mathcal{P}_2$'s strategy. The element a_{ij} of matrix A gives $\mathcal{P}_1$'s payoff when player $\mathcal{P}_1$ chooses strategy s_i and $\mathcal{P}_2$ chooses strategy t_j. The element b_{ij} of matrix B is $\mathcal{P}_2$'s payoff when player $\mathcal{P}_1$ chooses strategy s_i and $\mathcal{P}_2$ chooses strategy t_j. Since this type of game is defined by two payoff matrices, they are also called *bimatrix games.*

Games can also be divided into zero-sum and nonzero-sum [3]. If $a_{ij} + b_{ij} = 0, (\forall i \in 1, \ldots, m, \forall j \in 1, \ldots, n)$, then it is a *zero-sum game*, otherwise *non-zero sum* game. Note that the games in which $a_{ij} + b_{ij}$ is a constant are also categorized as zero-sum as they can be easily converted to zero-sum games. Zero-sum games are not called bimatrix games because only one player's payoff matrix is enough to define the game and the payoff matrix of the other player can be easily derived.

In a bimatrix game defined by the payoff matrices $A = [a_{ij}]$ and $B = [b_{ij}]$, a pair of strategies $\{s_i^*, t_j^*\}$ is said to constitute a *non-cooperative pure strategy (Nash) equilibrium solution* to the game if the following pair of inequalities is satisfied

$$\left\{ \begin{array}{l} a_{i^*j^*} \leq a_{ij^*} \\ b_{i^*j^*} \leq b_{i^*j} \end{array} \right. \quad \text{for all } i = 1, \ldots, m \text{ and all } j = 1, \ldots, n$$

It has been shown in [3] that a two-player nonzero-sum game may or may not have a pure strategy Nash equilibrium. Equilibrium can also be established with another form of strategy called *mixed strategy*, which means the equilibrium is established when at least one of the players has a "mix" of possible strategies. For example, if $\mathcal{P}_1$ has two strategies numbered as s_1 and s_2. A mixed strategy for $\mathcal{P}_1$ means he has a probability of p to choose strategy s_1, and a probability of $1 - p$ to choose strategy s_2. According to the definition, the mixed strategy makes sense only when the same game is played multiple times. It has been shown [3] that every bimatrix game has at least one Nash equilibrium solution in mixed strategies.

4.2 Why Non-cooperative and Nonzero-sum?

In this subsection, we justify why in an admission control game, the relationships between a service provider and its customers are non-cooperative and nonzero-sum.

First, in a competitive wireless data service environment, the relationship between a particular service provider and its customers is *non-cooperative* in nature. The service provider, on one hand, wants to maximize its own revenue. (Note that the service provider's attempt to maximize user's satisfaction, system utilization, etc., is merely an approach to achieve this ultimate goal of revenue maximization). So the revenue of the service provider is modeled as its payoff from this game. Users, on the other hand, want to maximize their own satisfaction with minimum expense, given that they have the freedom to leave the current service provider and subscribe to a better one in a competitive market. Thus the user's overall satisfaction is modeled as the user's payoff from the admission control game. Since these two goals are different and often conflicting with each other, the service provider and customers do not have the apparent motivation to cooperate with each other to achieve a single optimal goal. Single goal optimization, the approach undertaken by most of the existing works does not justify the optimality of the service provider's strategy for resource management that includes both admission control and rate control.

Second, the game is also *nonzero-sum.* In order to justify this, let us assume that the game is zero-sum in the sense that an increase in one player's payoff implies a decrease in the other player's payoff. However, this may not be true for the relationship between the payoffs of a wireless service provider and the customer. For instance, when the system is under utilized, admitting a new request that does not affect the QoS of other ongoing sessions, would increase the service provider's revenue as well as the customer's satisfaction. Thus, both the payoffs of the service provider and the user are increased, which conflicts with the zero-sum assumption. So this game has to be modeled as nonzero-sum.

4.3 Admission Control Game Formulation

Existing game theory based approaches to wireless network resource management consider the game played by multiple users in the system competing for the resources. In resource management problems such as power control, this is an appropriate model since the strategy chosen by one player (user), which is the power level he is using, has direct impact on the payoffs (SIR) of other users in the system. This implies direct interaction between multiple users under the same provider. The admission control problem is a little different in the sense that the direct interaction is between the service provider and the user seeking admission. So we choose to model the admission control as a game between the service provider and the user. However, the impact of admission control to other users cannot be ignored. The churn rate of the users already in the system and the corresponding revenue losses have been considered in the payoff of the service provider. More importantly, since the goal is to maximize the provider's revenue, the provider has to be one of the players participating in the game.

We formulate the admission control problem in wireless data networks as a two-player nonzero-sum, non-cooperative game. Admission control happens when a new session request is received by the system. The system then makes the decision whether to accept this request and allocate it a certain amount of resource, or reject it because of lack of resource. This decision making process is modeled as a game. We first adopt the one-by-one admission control mechanism in which the requests are processed one by one instead of as a bulk, i.e., one instance of the game is played every time a new session request comes into the system. The two players are the service provider (or the system that is processing this session request) and the customer that is currently requesting a session establishment.

The service provider has two strategies: SS_1 or admit the request, and SS_2 or reject the request. The customer seeking admission has two strategies as well: CS_1 or leave the current provider, and CS_2 or stay with the provider. The payoffs of these two players are expressed in the form of two 2×2 matrices $A = [a_{ij}]_{2\times2}$ and $B = [b_{ij}]_{2\times2}$, where a_{ij} and b_{ij} for $i \in \{1, 2\}$ and $j \in \{1, 2\}$, denote the provider's payoff and customer's payoff respectively, if provider chooses strategy SS_i and the customer chooses strategy CS_j. Before formally defining the payoffs for the service provider and the customer, we define some notations:

- U: the service provider's current revenue (utility) coming from all the on-going sessions.
- C_i: the service provider's average revenue per session in class i, for $1 \leq i \leq K$. This revenue depends on the class number (i.e., priority) of the session, the average

length of the session and the pricing scheme based on either time-usage based or traffic flow usage based.

- L_i: the service provider's average revenue loss for losing a class i customer, where $1 \leq i \leq K$. This is estimated based on the cost for the provider to gain a new customer into the system, assuming the provider's customer base is maintained constant.

- Pb_i: the predicted packet level blocking rate for class i customer, if the new session request is accepted. The *packet blocking probability* is defined as the probability that a frame coming from link layer is not immediately passed through the rate control unit because of inadequate power. Note that "blocking" here does not mean "dropping"; the frames are just blocked from immediate transmission. They are queued in the rate control unit for future transmission.

- $R_i(Pb_i)$: the class i customer's churn rate as a function of the packet level blocking rate. It is defined as a function of Pb_i because in the ARC framework, the customer's perceived QoS is mainly defined as the customer's packet blocking probability. The only data unit under consideration in this framework is the link layer packet, sometimes called frames. Packets and frames will be used interchangeably throughout this paper.

- N_i: the number of class i users currently in the system.

Assume a customer in class k is requesting a session admission. The provider's payoff matrix $A = [a_{ij}]_{2\times 2}$ is defined as follows:

$$A = \begin{bmatrix} U + C_k - F - L_k & U + C_k - F \\ U - L_k & U \end{bmatrix}$$

where $F = \sum_{i=k}^{K} N_i R_i(Pb_i) L_i$.

Let us discuss these payoff values. $a_{21} = U - L_k$ denotes the provider's payoff if it chooses strategy SS_2 and customer chooses strategy CS_1. This corresponds to the provider's strategy of rejecting the customer request and the customer's strategy of leaving the service provider. The payoff of the service provider in this case is the current revenue coming from all on-going sessions, minus the revenue loss due to the customer's churning. a_{22} is just the revenue from the current on-going sessions.

However, a_{11} and a_{12} need further discussion. a_{12} corresponds to the strategy pair (SS_1, CS_2), where the provider admits the request while the customer remains with the provider. This seems to yield the highest payoff for the provider. However, in a fully loaded system, admitting a new customer would either result in an infeasible power assignment (for cellular network providing voice service) [25], or delay of the current on-going sessions in the wireless data networks. Either of such cases may incur revenue loss because of churning of the customers whose on-going sessions are being affected. How exactly the on-going sessions are affected depends on the rate control mechanisms that are used in the system, which will be detailed in Section 5. The term a_{11} is defined in a similar way, just with one more term of $-L_k$ which corresponds to the revenue loss due to the customer's churning.

Admitting a new request into an already fully loaded system providing voice service is proved to be undesirable because it causes dropping of on-going sessions (calls). However, in CDMA wireless data networks, where infeasible power assignment can be avoided by reducing the transmission rates of on-going sessions, the pros and cons of admitting the new request need to be carefully evaluated in order to maximize the revenue for the service provider. We captured this aspect in the payoff value a_{11} and a_{12}. The term $N_i R_i(Pb_i) L_i$ gives the total predicted revenue loss for all class i users currently having on-going sessions. Our micro level rate control scheme, described in Section 5, ensures that when a class k user is admitted and the wireless resource is inadequate, only users of the same class or lower classes will be affected. Thus, $F = \sum_{i=k}^{K} N_i R_i(Pb_i) L_i$ measures the total revenue loss from all possible classes of users. The churn rate, $R_i(Pb_i)$, is obtained by applying Sigmoid utility function and discussed in detail in Subsection 4.4.

We define the user's payoff matrix $B = [b_{ij}]_{2\times 2}$ as follows:

$$b_{ij} = \begin{cases} w_1 U_{ij} - w_2 L_c & \text{for} \quad j = 1 \\ U_{ij} & \text{for} \quad j = 2 \end{cases}$$

where U_{ij} is the user's gain without considering churning and L_c is the customer's possible money loss if the customer chooses to churn. The term L_c comes from the fact that if the customer was still under contract with the service provider, he may be charged for early termination fee as a penalty. Subscribing to a new service provider may incur certain activation fee as well. L_c differs from user to user since some may be in contract while some others may not. The weights w_1 and w_2 on these two factors of user's payoff reflect user's preference on money saving and satisfaction maximization.

The user's gain, U_{ij}, without churning is given by:

$$U_{ij} = \begin{cases} R_k(Pb_k) + W_a & \text{for} \quad i = 1 \\ 0 + W_b & \text{for} \quad i = 2 \end{cases}$$

where W_a (or W_b) is the user's payoff when the request is admitted (or rejected). Obviously $W_a > W_b$.

It is well known that in a CDMA system, the forward link is power limited while the reverse link is interference limited [12]. We consider a system where the forward link traffic is the bottleneck because of the asymmetry of wireless data traffic. Thus the admission control and rate control are mainly performed over the power limited forward link, to ensure the stability of the system and maximization of the provider's revenue. The packet blocking probability, Pb_k, is only obtained for forward link. Since Pb_k is closely related to the packet level rate control, which regulates the traffic flows when full rate transmission of all on-going sessions is not possible due to the power constraint, we will discuss in Subsection 5 how to obtain Pb_k after the rate control mechanism is introduced.

The final decision on the admission control scheme as an outcome of our game formulation, is the *equilibrium* that is generally considered as the "best" solution to this type of non-cooperative games. We will discuss how to obtain the equilibrium in subsection 4.5.

4.4 Customer's Churning Rate

The customer's churning behavior is the key factor in formulating the proposed game for admission control. In this section, we derive the churn rates, R_i, for all user classes where $i = 1, 2, \ldots, K$.

The churn rate $R_i(\cdot)$, is defined as the probability that a class i customer leaves the current service provider. Thus, churn rate is a factor which is very much dependent on the (subjective) satisfaction of the customer and hence difficult to characterize mathematically. Therefore, we resort to the *utility* concept in economics to model this churn rate. Utility is a measure of customer's degree of satisfaction and can be modeled as a function of the quantity and quality of the merchandizes or services he receives, as well as the money he paid. Since we are not addressing any pricing strategies in this paper, we assume a session request means the customer is willing to pay for the session, and the utility is only a function of the service quality, which is Pb_i in our context.

The Sigmoid function [22] has been used to approximate the user's satisfaction with respect to service qualities or resource allocation [26] [23]. We slightly modify the Sigmoid function to incorporate the user's utility with respect to the packet blocking probability, Pb_i. Let O_i be class i user's utility. Then O_i as a function of Pb_i is given by:

$$O_i(Pb_i) = \frac{1}{1 + e^{-\alpha_i(\beta_i - Pb_i)}}$$

where α_i and β_i decide the steepness and the center of the curve. Both of them can be tuned to customize the function for different users. The value of α_i indicates the class i user's sensitivity to the QoS degradation (i.e., the increase in packet blocking), while β_i indicates the "acceptable" packet blocking probability for class i customer. In other words, with the increase of packet blocking probability, β_i decides when the utility decreases and α_i decides how fast the utility decreases.

Obviously the churn rate R_i is inversely related to O_i. This is because the more the user is satisfied, the less likely he is going to churn. We assume

$$\begin{aligned} R_i(Pb_i) &= 1 - O_i(Pb_i) \\ &= 1 - \frac{1}{1 + e^{-\alpha_i(\beta_i - Pb_i)}} = \frac{1}{1 + e^{-\alpha_i(Pb_i - \beta_i)}} \end{aligned}$$

Figure. 5 illustrates the user utility and the churn rate as functions of packet blocking probability, assuming $\alpha_i = 30$ and $\beta_i = 0.2$, which indicate that this user can tolerate a blocking probability of $Pb_i = 0.2$, and is not very sensitive to the blocking probability increase.

4.5 Equilibrium Solutions

In a bimatrix game, there may or may not be equilibriums in pure strategy, but the existence of at least one equilibrium in mixed strategy is guaranteed [3]. In our admission control game, we will show that pure strategy equilibrium exists for all cases. This property saves us from finding mixed strategy equilibriums which requires much more computation. Therefore, this property is very desirable for admission control, which requires the requests to be processed in real-time.

We study the equilibrium solution in two cases:

Case 1: $\forall i, Pb_i = 0, i \in \{1, \ldots, K\}$, which corresponds to the situation where the system is not full.

Case 2: $\exists i, Pb_i \neq 0, i \in \{1, \ldots, K\}$, which corresponds to the situation when the system is fully loaded (or overloaded) to certain extent.

We first show that in Case 1, our proposed admission control game is bound to have a Nash Equilibrium of pure

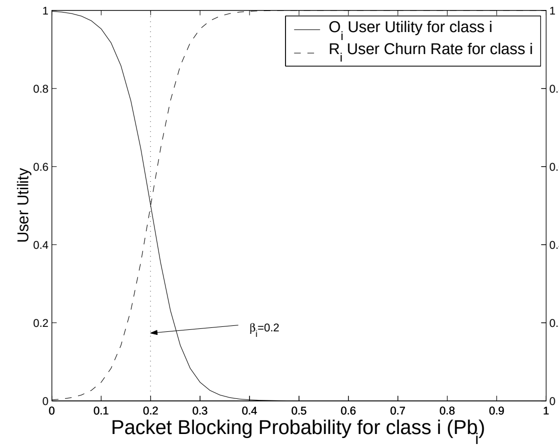

Figure 5: User Utility and Churn Rate

strategy in the sense that the strategy for the provider is to admit the call and that for the customer is to stay with the current provider. Formally:

THEOREM 1. *When $Pb_i = 0, \forall i \in \{1, \ldots, K\}$, the game has a Nash Equilibrium at strategy pair $\{SS_1, CS_2\}$, i.e., the service provider chooses to admit the session request while the user chooses to remain with the provider.*

PROOF. When the packet blocking probability $Pb_i = 0$, $\forall i \in \{1, \ldots, K\}$, the churn rate $R_i(Pb_i) \approx 0, \forall i \in \{1, \ldots, K\}$. Thus $a_{12} = U + C_k$. $a_{11} = U + C_k - L_k$, $a_{21} = U - L_k$ and $a_{22} = U$. In the provider's payoff matrix $A = [a_{ij}]_{2\times 2}$, $a_{12} > a_{11}$, $a_{12} > a_{22}$ and $a_{12} > a_{21}$.

Because $R_k(Pb_k) \approx 0$, the user's payoff matrix $B = [b_{ij}]_{2\times 2}$ is given by:

$$B = \begin{bmatrix} b_{11} = w_1 W_a - w_2 L_k & b_{12} = w_1 W_a \\ b_{21} = w_1 W_b - w_2 L_k & b_{22} = w_1 W_b \end{bmatrix}$$

Clearly $b_{12} > b_{11}$. Since $W_a > W_b$ as we mentioned while formulating the game, $b_{12} > b_{22}$ and $b_{12} > b_{21}$. Given that a_{12} and b_{12} are the maximum elements in matrices A and B, respectively, we conclude that strategy pair $\{SS_1, CS_2\}$ constitutes the Nash equilibrium to this game by definition. Furthermore, $\{SS_1, CS_1\}$, $\{SS_2, CS_1\}$ and $\{SS_2, CS_2\}$, these three strategy pairs do not yield equilibrium. □

In Case 2, where $\exists i, Pb_i \neq 0, i \in \{1, \ldots, K\}$, we show that there also exists a pure strategy Nash equilibrium, but the equilibrium point depends on values of certain terms in the payoffs.

Before discussing the equilibrium for this case, let us first introduce the concept of *dominant (or dominating) strategy* in game theory.

DEFINITION 1. *Let a bimatrix game be defined by two $m \times n$ matrices A and B, which are the payoffs of players $\mathcal{P}_1$ and $\mathcal{P}_2$ respectively. For player $\mathcal{P}_1$, we say that "row i"* dominates *"row k" if $a_{ij} \geq a_{kj}$, for $j = 1, \ldots, n$. Here "row i" is called a* dominant (or dominating) strategy *for player $\mathcal{P}_1$, and "row j" is called a* dominated strategy *for player $\mathcal{P}_1$.*

For $\mathcal{P}_1$, selecting the dominating "row i" is at least as good as selecting the dominated "row k". So "row k" can actually be removed from the game because $\mathcal{P}_1$ as a rational player would not consider this strategy at all.

The equilibrium for Case 2 is proved below.

THEOREM 2. *When $\exists i \in 1, 2, \ldots, K$, such that $Pb_i \neq 0$, the equilibrium strategy pair $\{SS_i, CS_j\}$ is defined as follows:*

$$i = \begin{cases} 1 & \text{if } C_k \geq \sum_{i=k}^{K} N_i R_i(Pb_i) L_i \\ 2 & \text{otherwise} \end{cases}$$

$$j = \begin{cases} 1 & \text{if } \{i = 1 \text{ and } b_{11} \geq b_{12}\} \text{ or } \{i = 2 \text{ and } b_{21} \geq b_{22}\} \\ 2 & \text{if } \{i = 1 \text{ and } b_{11} < b_{12}\} \text{ or } \{i = 2 \text{ and } b_{21} < b_{22}\} \end{cases}$$

PROOF. We prove this theorem for two subcases.

- $C_k \geq \sum_{i=k}^{K} N_i R_i(Pb_i) L_i$: in this case $a_{11} \geq a_{21}$ and $a_{12} \geq a_{22}$. By definition, SS_1 is the dominating strategy and SS_2 is the dominated strategy for the service provider. Since SS_2 can be eliminated, A and B degenerate into two 1×2 matrices. Obviously, if $b_{11} > b_{12}$, the customer will choose strategy CS_1, and if $b_{11} < b_{12}$ the customer will choose CS_2. When $b_{11} = b_{12}$, CS_1 and CS_2 have no difference to the customer. Without loss of generality, we assume the customer chooses CS_1. Hence, the equilibrium strategy pair is $\{SS_1, CS_1\}$ if $b_{11} \geq b_{12}$, or $\{SS_1, CS_2\}$ if $b_{11} < b_{12}$.
- $C_k < \sum_{i=k}^{K} N_i R_i(Pb_i) L_i$: in this case, $a_{11} < a_{21}$ and $a_{12} < a_{22}$. By definition, SS_2 is the dominating strategy and SS_1 is the dominated strategy for the service provider. Following the same logic in the above case, the equilibrium strategy pair is given by $\{SS_2, CS_1\}$ if $b_{21} \geq b_{22}$, or $\{SS_2, CS_2\}$ $b_{21} < b_{22}$.

□

The intuition behind Theorem 2 is that if the revenue C_k generated from accepting the new session request is greater than the possible revenue loss $\sum_{i=k}^{K} N_i R_i(Pb_i) L_i$ from the churning of the users, then admitting the session is a better strategy. Otherwise, the provider is better off rejecting the request. This gives the admission criterion for Case 2: $\exists i \in \{1, \ldots, K\}$ such that $Pb_i \neq 0$.

As mentioned earilier, a general bimatrix game may not have pure strategy equilibrium at all, though a mix strategy equilibrium is guaranteed. The significance of Theorem 1 and 2 is that they guarantee a pure strategy equilibrium solution for any instance of the admission control game formulated as above. Therefore, the system can make the admission decision simply by comparing certain terms in the payoff function, instead of searching for mixed strategy equilibrium, which is time consuming.

4.6 Formulation as n-player Game

Unlike what we assumed in the two player game, if the admission control is done in bulk, i.e., the admission control unit delays the session requests for a limited time, so that several requests can be processed in batch, the game changes from two-player game to n-player game. Let us now formulate such n-player games.

Assume n session requests are buffered and need to be processed at a time. This situation can be formulated as a $n + 1$ player game, consisting of the service provider and n users. Let the cth request belongs to a class $\mathcal{K}_c$ user. Based on either admitting or rejecting each individual request, the service provider has 2^n candidate policies, each of which can be represented by an n-element binary vector. The ith policy for the service provider (SS_i) is

$$SS_i = [s_{i1}, s_{i2}, \ldots, s_{in}]$$

where $s_{ic} \in \{0, 1\}$, $c = 1, \ldots, n$ and $i = 1, \ldots, 2^n$. $s_{ic} = 0$ means to reject the cth request and $s_{ic} = 1$ means to accept it. Each user still has two strategies. Let the τth user's strategy be CS_τ, $1 \leq \tau \leq n$, such that $CS_\tau = 1$ means the user leaves the service provider and $CS_\tau = 2$ means he stays with the provider. (Note that the meanings of the strategy notations are different than the two-player game.)

The payoff matrix A for the service provider and B_τ for τth user are now $(n+1)$ dimensional, with a size of $2^n \times 2 \times \ldots \times 2$, denoted as

$$\begin{aligned} A &= [a_{i,CS_1,CS_2,\cdots,CS_n}]_{2^n \times 2 \times \cdots \times 2} \\ B_\tau &= [b_{i,CS_1,CS_2,\cdots,CS_n}]_{2^n \times 2 \times \cdots \times 2} \end{aligned}$$

where the subscription i corresponds to the service provider's strategy, and CS_1, CS_2, ..., CS_n correspond to the strategies of the n users who are in the game.

The values of each element of matrices A and B_τ, i.e., the payoffs for the service provider and the τth user, are respectively given by

$$\begin{aligned} a_{i,CS_1,CS_2,\cdots,CS_n} &= U + \sum_{c=1}^{n} s_{ic} C_{\mathcal{K}_c} \\ &\quad - \sum_{l=1}^{K} N_l R_l(Pb_l) L_l - \sum_{\text{all } CS_c = 1} L_{\mathcal{K}_c} \\ b_{i,CS_1,CS_2,\cdots,CS_n} &= b_{(\frac{-s_{i\tau}}{2}+2),CS_\tau} \end{aligned}$$

Note that the payoff value for τth user is only dependent on the service provider's strategy to him ($s_{i\tau}$) and his own strategy CS_τ. This is because the individual customer does not have global information of whether other requests are admitted or not.

In the equation above, $b_{(\frac{-s_{i\tau}}{2}+2),CS_\tau}$ takes the same form of b_{ij} in the two-player game. For example, if in the ith service provider strategy the τth user's request is rejected ($s_{i\tau} = 0$), and the τth user's strategy is to leave the service provider ($CS_\tau = 1$), then $b_{(\frac{-s_{i\tau}}{2}+2),CS_\tau} = b_{2,1}$, which corresponds to the same strategy pair (b_{21}) in the two-player game defined in Subsection 4.3.

Though it is still possible to design the admission control in batch by formulating it to a $(n + 1)$ player game, the payoff matrix becomes complex and the way to find the equilibrium in two-player game is not applicable. In such a game, it is only guaranteed that at least one equilibrium exists in mixed strategy, but finding the equilibrium is computationally expensive. Moreover, for each service provider's strategy (remember there are 2^n service provider strategies), the system has to find the packet blocking probability, Pb_i, for all K classes, which is again computationally expensive and requires a lot of signalling from the power control unit. Since admission control has to be done in real time, in the rest of the paper, we will still use the two-player game formulation.

5. RATE CONTROL SCHEME

Since the admission control scheme in our ARC framework does not force a hard limit on the number of sessions that could be admitted into the system, it is possible that not all the sessions can get feasible power assignment to support their full rate transmission. We propose a rate control mechanism between the link layer and MAC layer so that the packets from certain sessions get buffered, such that transmission rate of those sessions can be reduced so that power limit is not exceeded.

Though the framework can support K classes of users, for the sake of simplicity, to show how rate control can be done for $K = 3$ classes of users: Premium (class 1), Gold (class 2) and Silver (class 3). Suppose there are currently N_i sessions in the system belonging to class i users where $1 \leq i \leq 3$. The data rate together with the bit error rate (BER) requirements can be mapped to the signal to interference ratios (SIR) depending on the multi access scheme and modulation technology used by wireless cellular system. This mapping is beyond our scope (refer to [19] for details). Although different users of the same class have the same SIR requirement, they may require different forward link power to maintain the necessary SIR due to different path losses and interferences they experience. Finding the feasible power assignment for the forward link is a power control problem and has been solved by existing work [25] [28]. We use one of the *standard power control schemes* [28] mentioned in [25] to find the power assignment vector $P' = [p'_1, p'_2, \ldots, p'_N, p'_{N+1}]$ after admitting the new customer. Assuming P_{max} as the maximal power a base station can transmit, when $\sum_{i=1}^{N+1} p'_i > P_{max}$, the rate control is initiated to ensure no more data than what the system can transmit, is fed into the MAC (Media Access Control) layer multiplexer.

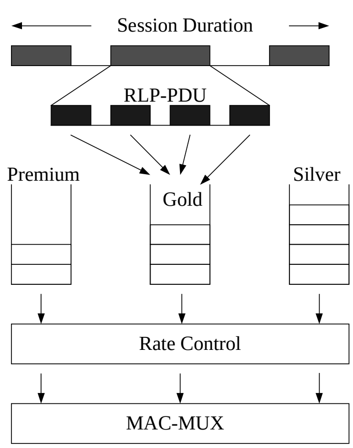

Figure 6: Controlling aggregated flows

As shown in Figure 6, in each base-station, the three aggregated forward link traffic flows of three classes are controlled through a gating mechanism. This dynamic rate control uses the estimate by the SIR measurements, to control the packet rate to the MAC layer multiplexer.

The burst level blocking is determined with the help of "on-off" state model of the traffic bursts. The bursts from a session by a Gold class customer is depicted in Figure. 6. The traffic bursts are segmented into RLP (radio link protocol) packets or frames [4]. The RLP packet data unit (RLP-PDU) is inserted into the respective class queue to be scheduled to the MAC layer through the rate control logic. Since the session illustrated in Figure. 6 is from a Gold class customer, the RLP-PDUs are inserted into the 'Gold' queue. The rate control has the capability of continuously measuring the SIR of the system. These SIR measurements indicate the average power (or energy) per bit required by the forward link to optimize the flow rate. Based on these measurements, the rate control is activated on a frame-by-frame basis. The rate control logic will use the frame level SIR measurements and determine how many RLP-PDUs can be transmitted within the optimal power per bit. Based on this calculation, it allows the RLP-PDU to go to the MAC-MUX. The power control algorithm at the MAC layer is not affected by this control mechanism. The MAC layer gets the number of RLP-PDU frames that can maximize the throughput of the system.

The basic idea of the proposed rate control scheme is to reduce the transmission rate of users in the same class as well as lower classes, so that the power limit is not exceeded. Assume that there are N_i users of class i, where $1 \leq i \leq 3$. Let the average power required for each user in these classes be $\overline{P_i}$, for $1 \leq i \leq 3$. Define power shortage D as:

$$D = \sum_{i=1}^{3} N_i \overline{P_i} - P_{max}$$

Since class 1 (Premium) is defined as the class with the highest priority, the rate for users in lower classes have to be reduced to yield extra power for class 1 users. The total power budget for class 2 and class 3 users are given by:

$$Pt_2 = N_2 \overline{P_2} - \gamma D, \quad Pt_3 = N_3 \overline{P_3} - (1 - \gamma) D$$

where γ is a tunable parameter determining the ratio in which the power is contributed from these two lower classes. According to the reduced power budget and the system measurement of energy per bit, the reduced rate for each user can be calculated and maintained by the rate control unit as shown in Figure. 6.

The blocking probability, Pb_i, for class i user, is determined by assuming the "on-off" model on the source traffic. It is assumed that the data packets (e.g., TCP, UDP) will arrive to the Base Transceiver System (BTS) from the gateway server or directly from the content server (see Figure. 3). The average power per source required for the Gold class at any instant is obtained from the system measurement. This measured average power is used to determine the blocking probability. If N'_2 is the average permissible number of customers of class 2 with full rate transmission, then $N'_2 = Pt_2 / \overline{P}_2$. Similarly, $N'_3 = Pt_3 / \overline{P}_3$ for class 3 users. If $N'_2 \geq N_2$, then $Pb_2 = 0$, otherwise Pb_2 has to be calculated considering the probability of more than N'_2 bursts at any instant of time.

Let ρ be the probability of a session being in the "on" mode. Then the packet blocking probability for class 2 users is given by

$$\begin{aligned} Pb_2 &= \text{Prob.}\{\text{\# of sessions in "on" mode} > N'_2\} \\ &= \sum_{j=N'_2}^{N_2} \binom{N_2}{j} (\rho)^j (1-\rho)^{N_2 - j} \end{aligned}$$

The blocking probability (Pb_3) for class 3 users can be ob-

Table 1: Simulation Parameters

Parameter	Value	Parameter	Value
L_1	150	T_{hold}	100 sec
L_2	100	L_c	30
L_3	50	W_a	5
C_1	0.35	W_b	1
C_2	0.15	ρ	0.3
C_3	0.05		

T_{hold}: Average Session Holding Time.

tained similarly.

The performance of our proposed framework is evaluated in the following section.

6. PERFORMANCE EVALUATION

We developed a simulation platform to evaluate the performance of the ARC framework. Assume that there are more than one service provider in the wireless data market, and one of the providers uses the proposed ARC framework. Though only the operation of the provider utilizing ARC framework is simulated, the market competitiveness is take into account in the user's churn rate, since a single provider market has no churning or at least its impact is so small that it could be ignored.

The simulated system has a session request generator and a resource management framework, which consists of an admission control unit at the macro (session) level and a rate control unit at the micro (packet) level. A built-in power management unit in the simulation estimates the required power for each class and allocates power to each user. The state of this unit is updated on a frame-by-frame basis. (We assumed 20 ms frames). The values of the parameters used in the admission control game simulations are defined in Table 1.

We still use three classes of users as defined in Section 5 in our simulation. We assume that the arrivals of session level call admission requests follow Poisson Distribution with arrival rate $\lambda = \lambda_1 + \lambda_2 + \lambda_3$, and also $\lambda_1 = \lambda_2 = \lambda_3$, where λ_i $(i = 1, 2, 3)$ is the arrival rate of class i users.

We conducted extensive simulations to test the performance of the ARC framework. The performance is evaluated in terms of packet delay, queue length, session level blocking rate and revenue generation. The expected queue length and packet delay are measured to evaluate the performance of micro level rate control, while the request blocking probability is measured to evaluate the performance of macro level session admission control. Finally, we present the revenue improvement provided by the proposed ARC framework.

6.1 Expected Queue Length and Delay

The transmission delay is directly related to the queue length in each class. With the total queue length, we are able to estimate the RLP frame delay. According to Little's theorem, $Q = \lambda T$ where Q is the total number of packets in the queue, λ is the RLP frame arrival rate, while T is the average time the RLP frames spend waiting in the queue. Because different classes of users have different RLP frame queues, the delay of each frame of class i $(1 \le i \le 3)$ can be estimated as $T_i = \frac{Q_i}{\lambda_i}$, where Q_i is equal to the average queue length of class i and λ_i is the average number of frames that users of class i request to transmit during each frame time. Thus $\lambda_i = E[N_i]\rho$, where $E[N_i]$ is the average number of users in class i and ρ is the active rate of the source in the "on-off" model.

The expected RLP frame delay and the expected total queue lengths of each class are shown in Figure 7 and Figure 8 respectively. It is observed that when the arrival rate is high, though Silver and Gold class have shorter queue length, they have longer delay than the Premium class. The delay difference between Premium, Gold and Silver users shows that the system does a good job providing differentiated quality of service (QoS) to each class of users.

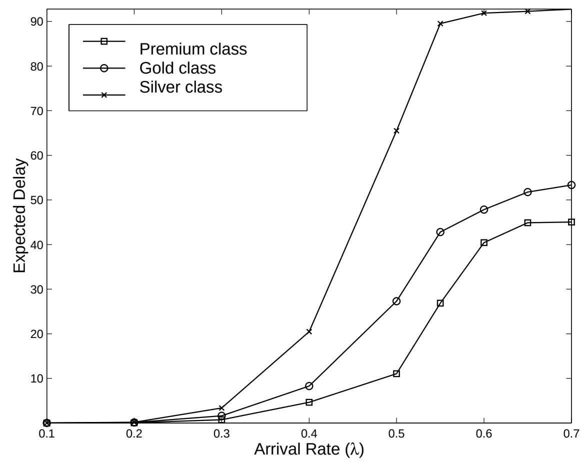

Figure 7: Expected Delay vs. λ

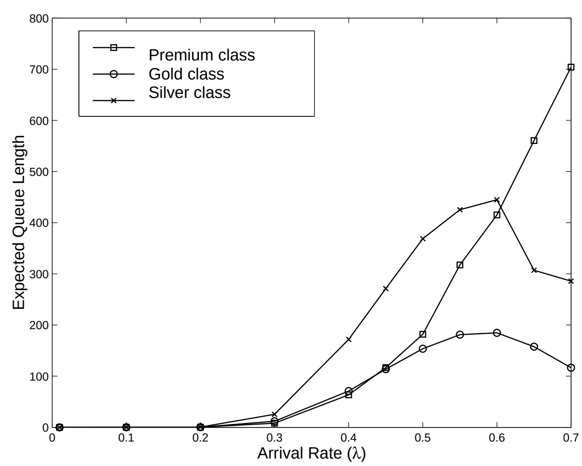

Figure 8: Expected Queue Length vs. λ

6.2 Session Request Blocking Rates

The relationship between the session request blocking rate and the arrival rate λ is shown in Figure 9. The total session arrival rate is $\lambda = \lambda_1 + \lambda_2 + \lambda_3$, which represents the aggregate session arrival rates for Premium, Gold and Silver classes. We design the cellular data system to be able to support $N = 100$ sessions at the same time on an average. Since we assumed $\rho = 0.3$ (Table 1), the system can handle on average a session arrival rate of 0.3 requests per second, above which significant session blocking will occur. We let λ vary from 0.01 to 0.7. In other words, the arrival rate varies from very light load (almost 0) to very heavy load (about twice as much as the system can support). It is observed that the system gives much higher priority to the Premium class users; the rejection rate for this class is never more than half of the rejection rate of Gold and Silver classes. But the rejection rates of Gold and Silver classes do not seem to have any difference at all.

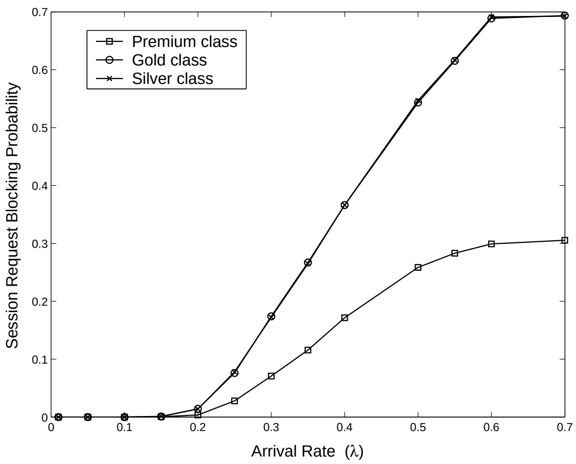

Figure 9: Request Blocking Probabilities

6.3 Revenue Comparison

In order to show whether the proposed ARC framework can achieve higher revenue for the service provider, we compared the proposed system with a reference system having a simple admission control scheme. The simple scheme is designed to admit a request if the total number of users $N' = N'_1 + N'_2 + N'_3$ in the system after admitting the new request does not exceed the total number of users that the system can serve. All other details of the reference system are the same as our proposed ARC system. The comparison is based on revenue generated by each system operating for 24 hours. The total revenue of each system is calculated by summing all the revenue gathered from the sessions admitted into the system, minus the revenue loss (L) caused by the users' churning due to unsatisfied service. Figure 10 shows the revenue differences between the two systems, as well as the percentage of revenue improvement in the ARC framework.

It is clear that when the arrival rate approaches and/or exceeds the full capacity of the system, i.e., $\lambda \geq 0.3$, the proposed ARC system gathers much more revenue than the reference system considered. The revenue improvement is as much as 40% in the proposed system. Figure 11 shows the total number of accepted requests during the 24-hour period. The merit of our proposed framework is this: though the total number of requests accepted is almost the same or slightly less, our system generates more revenue than the reference system in high load situation. In other words, the proposed ARC system is capable of identifying the pros and cons of selectively accepting requests to generate more revenue.

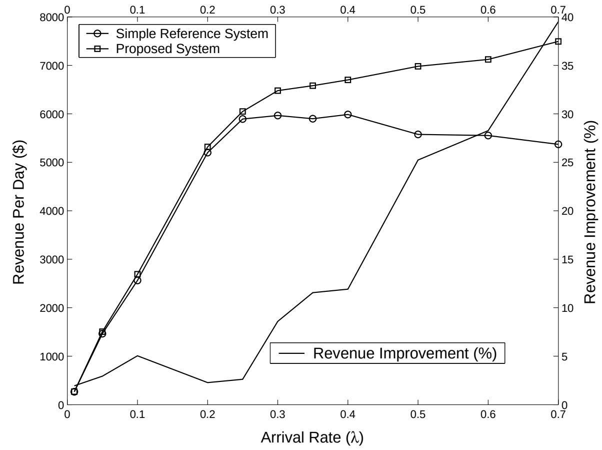

Figure 10: System Revenue vs. λ

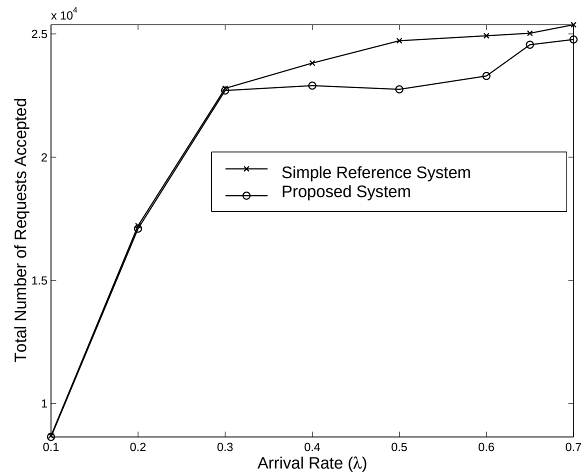

Figure 11: Total Accepted Requests vs. λ

7. CONCLUSIONS AND DISCUSSIONS

In this paper, we proposed an integrated framework of **A**dmission and **R**ate **C**ontrol (**ARC**) for CDMA data networks using game theoretic approach. The framework is able to provide differentiated data services to multiple classes of users. We formulated the admission control problem as a non-cooperative two-player nonzero-sum game between the service provider and the customer. We show that Nash equilibrium can be established both in under-loaded system and fully loaded system. Not only the revenue generated but also the risk probabilities of customers leaving the network, (i.e., churning), are considered in the service provider's payoffs from the game. Integrated with the admission control we propose a rate control mechanism so that the users' QoS is differentiated and the power budget is maintained by allowing higher classes to draw resources from the lower classes, when the power is not enough to support full rate transmission for all users. The simulation results show that by incorporating the users' churning behavior in a competitive wireless data network environment, the proposed framework can achieve higher revenue for the service provider, and also yield differentiated QoS to different classes of users.

Let us discuss additional issues that can be explored as a natural extension to this work.

- The possibility of employing n-player game formulation in admission control. It is our intuition that if an efficient optimal or sub-optimal algorithm to compute the equilibrium in mix strategy can be formulated, the performance of the admission control can be further improved. This is because, by considering batch requests at a time, the session request selection changes from "local" (only one request) to "regional" (more than one request). This granularity may yield better admission strategies for revenue maximization. However, this is at the cost of delayed request response since some requests will be buffered for a certain duration before being served.

- How to enhance the rate control mechanism and modeling it as a multi-player non-cooperative game between all the users in the system, find mechanisms to customize the user churn rate function as the game evolves, and attempt to formulate games directly between multiple service providers?

- There might be concerns about the unstable dynamics of the user subscriptions. For example, there might be bang-bang effect that a user signs on a service provider for a short while, then signs off, and again signs on. The effect of such dynamics will depend on the *relative rate* of user churn and system updates. Note however the resource management in ARC framework takes place in a very different time scale than the user subscription behavior. Usually users change service provider every half year, or a year. A considerable amount of users may not change the service provider for years. That is why we define the churn rate as a probability. It is possible such bang-bang effect happens, but if the user base fluctuates in a time scale of months, it is unlikely to cause significant problem for the real time resource management framework. This kind of dynamics will have impact on the the resource management if in the future the users are able to subscribe to wireless service on a session basis, which means the users are free to select the service providers when he needs a connection. In this case, multiple service providers will be included in an admission control game. We expect this to be a very interesting case to analyze and will work on it.

- Use some other cost/revenue functions, for which Theorem 1 and Theorem 2 may not hold, thus requiring us to search for equilibrium of mixed strategy. With better cost/revenue models, the proposed framework will be more attractive to the service providers economically.

- Explore if some of the functions in the ARC framework can be incorporated into the ns-2 wireless packages to achieve more realistic traffic and results. ns-2 provides very good data traffic simulations. At this time, we chose not to use ns-2 because it does not have good support for cellular wireless network simulations, not to mention the CDMA air-interface, and developing these parts in ns-2 is more time consuming than stand-alone simulations. Moreover, for this paper, the simulation is only for illustrative purpose, so we did it in a stand-alone fashion.

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