THE PRICE OF NON-COOPERATION IN RESERVATION-BASED BANDWIDTH SHARING PROTOCOLS

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ABSTRACT

In reservation-based bandwidth sharing protocols, the base station relies on the stations' requests to allocate time slots to them. Like most other protocols, reservation-based protocols were designed with the assumption that all stations respect the rules of the protocols. However, as mobile devices are becoming more intelligent and programmable, they can selfishly optimize their operations to obtain a larger share of common bandwidth. Here, we study reservation-based bandwidth sharing protocols considering the existence of selfish stations through game-theoretic perspectives. We show that this game admits a Nash equilibrium. Then, we prove the inefficiency of the Nash equilibrium. Game-theoretical analysis shows that local optimization in the bandwidth sharing problem with conflicted interests does not lead to any global optimization.

Keywords. Nash equilibrium, Repeated game, Reservation-based.

1. INTRODUCTION

With the rapid growth of personal networking, the demand for services in a mobile environment has been growing faster and more diverse. New protocols for personal communication must account for the presence of several different classes of traffic with diverse patterns and quality of service (QoS) requirements, and make sure that those applications coexist as comfortable as possible within the restrictive framework of mobile environment. The major advantage of reservation-based algorithms is that they provide a significant reduction in the number of collisions incurred during communication. Moreover, reservation-based protocols are very power efficient that is inherently collision free and avoids unnecessary idle listening, which are two major sources of energy consumption.

Many reservation-based access protocols have been proposed for mobile networks, e.g. [1 - 6]. All the protocols mentioned above use a similar channel structure. Time on the uplink channel is divided into timeframes, and each timeframe is divided into a number of transmission slots and a number of possibly smaller minislots used for contention resolution. Transmission slots may be fixed or varied in length depending on protocols. Those approaches are efficient if all stations play by the rules of the protocols. However, we claim that this assumption is less and less appropriate, because the network adapters are becoming more programmable [7].

Despite the vast of work invested in improving reservation-based protocols, all of the studies of reservation-based protocols have ignored the system performance in the presence of selfish users. In this paper, we study the stability and efficiency of reservation-based protocols in wireless networks that contain selfish users. By *selfish* we designate the users who are ready to tamper with their wireless interface in order to increase their own share of the common transmission resource. We assume these users to be rational, and not intend to harm other users without deriving a benefit from this misbehavior. The main motivation of this work is to study the performance of the system with selfish stations and design reservation-based access methods that could stabilize the network around a steady state at which the stations' performance is fair and high efficiency.

We first recall some basic concepts of game theory. A normal game is defined by a tuple *(players, strategies, utility functions)*, each player has a set of strategies to choose, called *strategy space*, a utility (*payoff*) function of a player takes as input a *strategy profile* (a specification of strategies for every player) and yields a representation of utility as its output. A *Nash equilibrium* of a game is when there exists a *strategy profile* which fully specifies all actions in a game - such that no player could gain more by unilaterally changing its strategy. In a game there may exist many Nash equilibria, so that the *social profit* (sum of players' utilities) of the game at each Nash equilibrium may get different values. The *price of anarchy* (PoA) is the ratio between the worst Nash equilibrium and the (social) optimal solution, and the *price of stability* (PoS) is the ratio between the best Nash equilibrium and the (social) optimal solution. Hence, when the system is at a Nash equilibrium then PoA is the lower bound, and PoS is the upper bound for the difference between the social profit at a Nash equilibrium and the optimal solution.

In this work, we consider that a selfish station makes use of the easiest cheating technique: he reserves for a larger time slot to maximize its throughput. Although this cheating technique is straightforward, we show that studying its implications is far from trivial. In order to investigate the system with selfish stations, we make use of *game theory*. Here, we define a new game, named *reservation game*. In this game, each station is a *player*, the throughput it enjoys is its *payoff*, and its request represents its *strategy*. With assumption that the allocation scheme of the base station is fixed and public to every stations, we study the system where stations are players who compete for the bandwidth. We model this problem as a *repeated game* [9]. Analysis shows that the dynamic *best response* of players will make the system converge to a *Nash equilibrium*.

We organize this paper as follows. In section 3, we define the problem and point out an optimal solution of it. Section 2 reviews game-theoretic approaches to channel access protocols. In section 4, we formulate the Reservation game, we prove for the existence of Nash equilibrium as well as the bound of price of anarchy. We conclude in section 5.

2. PRIOR WORK

Recently, much work on MAC layer protocols takes into account the selfish players. However, prior work on reservation-based protocols in wireless networks doesn't consider the selfish behavior mobile stations. Slotted ALOHA and CSMA are two most popular MAC protocols which are investigated through gametheoretic perspectives.

One of the earliest applications of game theory to medium access protocols is the work of Zander in [12] and [13]. However, the game is considered in cooperative nature and does not consider contention among selfish stations themselves. For the games in which players selfishly contend for the channel, researchers approach those problems in many different types of games.

In the ALOHA games, many researchers formulate the problem as a *repeated game* [9] such as the work of MacKenzie et al. [14], Y. Jin et al. [15]. The *Stochastic game* [9] model is applied in the work of MacKenzie et al. [16], and Altman et al. [17]. Y. Cho et al. use *single-*

stage Bayesian game [9] to approach the ALOHA game for the wireless networks in fading environments in [18]. Recently, R. Ma et al. [19] model the Aloha game as a *Stackelberg game* [9], where one of players is voted to be the leader and other players are followers.

In the CSMA games, L. Chen et al. [20], and M. Cagalj et al. [11] use both static game and dynamic game to approach the problems of medium access control with selfish stations. The repeated game model is again used in the work of Konorski [10], and L. Galluccio [21]. Y. Cho et al. [18] applied single stage and multistage Bayesian game models for the CSMA protocols in fading environments.

In most cases of contention game with non-cooperative context in fully distributed environments, the games admit the Nash equilibria. Yet, these equilibria do not possess any type of global optimality or even paralyze it complete. In cooperative situations, Pareto efficient points are preferred for the protocol design's target. Unfortunately, participants in wireless networks hardly cooperate in distributed environments, and Nash equilibria need not to coincide with Pareto-optimal points. More details are discussed in following sections.

3. SYSTEM MODEL

We consider n wireless stations in the same cell that are willing to transmit data to designated receivers. Stations share the same uplink bandwidth. We ignore the downlink because it is only used by the base station. Time is divided into many frames. The uplink frame structure used here, like the work of Zhang et at [4], is shown in Figure 1. The frame is divided into two sections. The first (reservation) section consists of a sequence of minislots used by stations to issue access requests. We assume that each station is associated with a single minislot so that there is no collision in this section. If a station doesn't have data to send in this frame it has to send a request with zero time slot size. To do this, base station ensures that there is no collision attack from misbehavior stations during reservation section. The second (transmission) section, *transmission time* is dynamically partitioned into a number of variable-length time slots according to how the bandwidth allocated to the mobile stations.

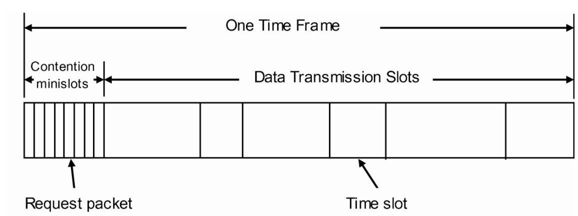

Figure 1. Uplink frame structure

At beginning of each frame, stations move data from input buffers to output buffers and send requests based on the current data in their output buffers. We assume that if a station doesn't get enough time slot to transmit its data then it will drop all remain data in its output buffer.

We consider the system with many different classes of traffic, assuming that each station i has arrival rate λ_i , and the packet loss probability of user i is given by a *loss function* $f(r_i)$, where r_i is the *relative rate* of station i. The relative rate is the fraction of transmission slot assigned to the station, normalized to his arrival rate. That is if station i gets p_i fraction of transmission slot ($\sum_i p_i = 1$), then $r_i = p_i/\lambda_i$. It is reasonable to assume the loss function $f(r_i)$ satisfies the two following general conditions:

1. Increasing the allocated bandwidth for any given station decreases its loss. That is, $f(r_i)$ is a strictly decreasing function of r_i .
2. For any station and any allocated bandwidth, the additional gain (i.e. loss decrement) obtained by a given absolute increment in the allocated bandwidth gets smaller as the *relative* increment decreases. This means that the more resources a station has already, the smaller additional gain he will obtain by receiving a fixed increase added to his allocated resources.

Two above conditions imply that the loss function is convex, detailed proof is in [8]. Now we compute the relative rates that maximize the throughput. We consider the equivalent problem of minimizing the total loss

$$L - \sum_{i=1}^{n} \lambda_i f(r_i) \tag{1}$$

under the constraint that the fractions of transmission slot, given the the respective stations, sum up to 1.

Theorem 1 [8]. *The* $\sum_{i=1}^{n} \lambda_i f(r_i)$ *achieves its minimum if and only if the relative rates of the stations are equal to each other, i.e.*

$$r_1 = r_2 = \cdots = r_n = \frac{1}{\sum_{i=1}^{n} \lambda_i} \tag{2}$$

***Proof*.** See [8] for detail.

However, if the stations don't report their true arrival rates then Theorem 1 is no longer guarantee for the system optimal throughput. To obtain more share of bandwidth, the selfish stations may report more than their real arrival rates. Thereupon, some selfish stations could optimize their throughput. While honest stations which report true arrival rate have to lose more data. Hence, system throughput cannot achieve optimal or fairness any more. In next section, we study insight into the reservation-based protocols considering the existence of selfish stations through game-theoretic perspectives.

4. RESERVATION GAME

4.1. Game model

Through this game, the base station makes use of the allocation scheme as in Theorem 1 and it is public to all stations. By this allocation scheme, a station could declare higher arrival rate to receive a larger share of bandwidth.

The data amounts of stations depend on their arrival rates. When stations transmit some data, they will receive some *profit*. Specifically, we define the profit function $v(x) : \mathbb{R}^+ \to \mathbb{R}^+$ with *x* is input data as follows:

$$v(x) = \begin{cases} \alpha x, \text{ if } x \text{ are data packets, constant } \alpha > 0 \\ 0 \quad \text{if } x \text{ are dummy packets} \end{cases} \tag{3}$$

The profit function means that a station gets no profit if it just transmits dummy packets or doesn't transmit, the more data it transmits the more profit it obtains, hence, this is a non-decreasing function. Besides, stations have to pay for some *cost* $c(x) : \mathbb{R}^+ \to \mathbb{R}^+$, e.g. energy consumption. Precisely:

$$c(x) = \gamma x, \text{ constant } \gamma \geq 0. \quad (4)$$

To motivate stations to transmit their data, we assume that the profit is larger than the cost they have to pay for any transmitted data amount, i.e. $\alpha > \gamma$. We define stations' *utilities* as:

$$u(x) = v(x) - c(x). \quad (5)$$

By above definition, we see that the more data stations can send, the higher utilities they gain. The utility function can be drawn as Figure 2.

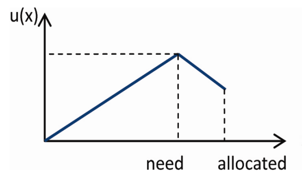

Figure 2. Utility function

Stations' objective is to maximize their utilities. We easily see that stations achieve optimal utilities if and only if their allocated bandwidth is equal to what they need.

Let each station be a *player*. In the reservation section, a player *i* chooses his *strategy* $w_i \in [0, W]$, that is the data he declares to the base station, and *W* is the frame's capacity. A *configuration profile* $w = (w_1, ..., w_n)$ is a specification of strategies for every player. For the sake of simplicity, we assume that every station has the same transmission rate, and each station needs a time slot *x* to transmit an amount *x* of data. We will denote $(w_1, ... w_{i-1}, w_{i-1}, ... w_n)$ by w_{-i}. And $w = (w_{-i}, w_i)$ will denote the tuple $(w_1, ..., w_n)$. We now define the reservation game.

Definition 1. A reservation game is *a tuple* ({1, ..., n}, $[0, W]$, u), *where* {1, ..., n} *is the set of players (stations),* $[0, W]$ *is the set of feasible strategies (i.e. what stations can declare), and* u : $[0, W]^n \to \mathbb{R}$ *is the utility function. Each station i selects a strategy* $w_i \in [0, W]$ *and subsequently receives a utility* $u_i(w)$ *dependent on the configuration profile* $w = (w_{-i}, w_i)$.

We first study the existence of Nash equilibria points. At a Nash equilibrium, every player chooses his *best-response* strategy, i.e. given a set of strategies of other players w_{-i} , player *i* will choose the strategy w_i such that it maximizes his utilities. Formally, a Nash equilibrium is defined as follows,

Definition 2. *A Nash equilibrium* (NE) *is a configuration profile* $w = (w_{-i}, w_i)$ *at which* $u_i(w) \geq u_i(w_1, ... w_{i-1}, w_{i+1}, ... w_n)$ *for all i = 1, ..., n and* $w'_i \in [0, W]$.

At a NE, each player selects his best response to the other players' strategies, a likely outcome if all the players are rational. However, when the system is at a NE point, networks are collapsed in most of the cases, e.g. the results in [10], [11]. Therefore, a fair and efficient configuration profile is a desirable outcome as a form of "cooperative equilibrium". Let us define the *Pareto efficient* profile as follows:

Definition 3. *A configuration profile* $w \in [0, W]^n$ *is* Pareto inferior to *another configuration profile* $w' \in [0, W]^n$, *if* $u_i(w) \leq u_i(w')$ *for all i = 1, ..., n with at least one strict inequality. It is Pareto efficient if it is not Pareto inferior to any other configuration profile, and fair if* $u_1(w)$ = ... = $u_n(w)$.

That is, a Pareto efficient outcome cannot be improved upon without hurting at least one player. From the global performance viewpoint, a fair and Pareto optimal configuration profile is a desirable outcome in the cooperative context. Unfortunately, it does not need to coincide with a NE. We take an example with the remark below.

Remark 1. Let λ_i be arrival rate of station i, the configuration profile $w = (w_1, \dots, w_n)$ where $w_i = \lambda_i$ for all *i* = 1, ..., *n*, and base station allocates to station *i* a fraction of bandwidth $p_i = \frac{w_i}{\sum_{j=0}^{n} w_j}$ for all *i* = 1, ..., *n* is a Pareto efficient profile. However, this configuration profile needs not a Nash equilibrium.

Intuitively, if $\sum_{i=1}^{n} w_i \leq W$, then the system can satisfy all requests. In other words, all stations achieve their optimal utilities.

Otherwise, $\sum_{i=1}^{n} w_i > W$, then the allocation scheme where each station i receives a fraction $p_i = \frac{w_i}{\sum_{j=0}^{n} w_j}$ of bandwidth is the optimal solution by *Theorem 1*. As our assumption, at a given profile $w, u_i(w)$ is an increasing function, it means that if a station *i* receives more time fraction $p_i(w)$ then it gets higher throughput. For any configuration $w' = (w'_{-i}, w'_i)$, if there exists station *i* such that $u_i(w') > u_i(w)$, then to prove that profile w is Pareto efficient, we show that there exists station *j* such that $u_j(w') < u_j(w)$. Since $u_i(w') > u_i(w)$ implies that $p_i(w') > p_i(w)$. We have $\sum_{i=1}^{n} p_i(w) = \sum_{i=1}^{n} p_i(w') = 1$, so that there exists *j* such that $p_j(w') < p_j(w)$ which implies $u_j(w') < u_j(w)$.

The game admits Pareto optimal profile, however, players may improve their utilities by deviating from their true reports ($w_i = \lambda_i$) to get higher bandwidth when the system doesn't have enough bandwidth for all stations, i.e. this profile is not a Nash equilibrium.

Before studying the existence of Nash equilibria, we assume that the base station cannot recognize selfish stations by examining their packets or monitoring their traffic. Because stations may encrypt their data, and also send dummy packets to fill up extra reserved time slots. Hence, stations can avoid the detections and penalties. In addition, we assume that the system is not always *overload* or *underload*. We define an *overload/underload* frame as follows:

- *Overload frame:* total requests is larger than frame capacity

- *Underload frame:* total requests is not larger than frame capacity

At the beginning of each timeframe, stations reserve the bandwidth by sending their requests to the base station. Let each frame be a *game stage*, a station can base on the state of previous game stage to make request in current stage. We, hence, model this problem as a repeated game. This means that this stage game is played repeatedly. If players are not sure when the game will end, we can model this as an infinitely repeated game. The repeated game is assumed to be discounted, i.e. the utility received at stage *n* is discounted by δ^n for some $\delta < 1$. Players want to maximize their long term utilities, i.e. maximizing the total of utilities that they receive in each single game stage.

4.2. Properties of a single Stage Game Nash equilibrium

Game stage is an underload frame. In underload frame, stations receive bandwidth as they requested. Therefore, a station with truthful strategy (requests as its need) achieves maximum utility. This means that the strategy profile $w = \{w_1 = \lambda_1, w_2 = \lambda_2, \ldots, w_n = \lambda_n\}$ is a Nash equilibrium.

Game stage is an overload frame. In this case, the best response of stations will converge to a stable state which is also a Nash equilibrium.

The institution is that a player *i* can obtain at least $1/n$ fraction of bandwidth with strategy $w_i = W$. Therefore for a player *i* who needs less than $1/n$ bandwidth then he finally finds his optimal strategy, say $w_i^* < W$, to achieve his optimal utility. For players who cannot obtain enough time slots for their need then they eventually reach strategy W at which players get as much utilities as possible. When a player either gets its maximum utility or its strategy is at maximum value W then the system is stable. Because, at this point, no players can increase their utilities by changing their requests. Thus, this stable state is also a NE profile. If stations have different arrival rates, it's clearly that this NE profile is neither a fairness nor an optimal system throughput.

4.3. Existence and convergence of Nash equilibrium

Lemma 1. *If the system state is stable in either underload or overload for sufficient long, the best response of players converge to a Nash equilibrium.*

Proof sketch. Each game stage is either an underload or an overload frame. At a transition frame (changing from overload to underload frame or vice versa), a player with the strategy as the previous game stage would lose some utility. However, if the current state stays long enough (meaning that δ is sufficiently close to 1), this loss will be overweighted by the gain in every subsequent period. This intuition means that in either game state, the system converges to a Nash equilibrium eventually.

4.4. Bound on Price of Anarchy

At a Nash equilibrium, some stations might obtain enough bandwidth for their transmission, e.g. stations require less than $1/n$ fraction of bandwidth. Other stations would share the equal fraction of remain bandwidth. Thus, we have the price of anarchy of this game as below.

Lemma 2. *The price of anarchy is bounded by* $\lambda_{max}/\lambda_{min}$ *, where* λ_{max} *,* λ_{min} *is the maximum, minimum arrival rate, respectively.*

Proof. Without loss of generality, we assume that $\lambda_1 \le \lambda_2 \le \ldots \le \lambda_n$. By *Theorem 1*, a station *i* receives a time slot proportionally to its arrival rate at the optimal solution, so that its throughput is $\lambda_i(1 - f(\eta_i))$ where $\eta_i = \frac{1}{\sum_j \lambda_j}$. Then the optimal system throughput is:

$$\Theta_{OPT} = \sum_{i=1}^{n} \lambda_i (1 - f(\eta_i)) \quad . \tag{6}$$

In a Nash equilibrium, let each station $i \in [1,\dots,k]$ obtains δ_i fraction of bandwidth with some strategy $w_i < W$. We note that $\delta_i < 1/n \ \forall i \subset [1,\dots,k]$, let $\Delta \equiv \sum_{i=1}^{k} \delta_i$. While each station $j \in [k+1,\dots,n]$ receives an equally $\frac{1-\Delta}{n-k}$ fraction of bandwidth. Note that $\frac{1-\Delta}{n-k} \geq 1/n$. Thus, total throughput at a NE is:

$$\Theta_{NE} = \sum_{i=1}^{k} \lambda_i (1 - f(\frac{\delta_i}{\lambda_i})) + \sum_{i=k+1}^{n} \lambda_i (1 - f(\frac{1-\Delta}{(n-k)\lambda_i})). \quad (7)$$

Since stations $\in [i,\dots,k]$ in a NE receive more bandwidth than those in optimal solution, we have:

$$\sum_{i=1}^{k} \lambda_i (1 - f(r_i)) \leq \sum_{i=1}^{k} \lambda_i \left(1 - f(\frac{\delta_i}{\lambda_i})\right). \quad (8)$$

Hence,

$$\frac{\Theta_{OPT}}{\Theta_{NE}} \leq \frac{\sum_{i=k+1}^{n} \lambda_i (1 - f(r_i))}{\sum_{i=k+1}^{n} \lambda_i (1 - f(\frac{1-\Delta}{(n-k)\lambda_i}))}$$

because,

$$\frac{1-\Delta}{n-k} \geq \frac{1}{n} \Rightarrow f(\frac{1-\Delta}{(n-k)\lambda_i}) \leq f(\frac{1}{n\lambda_i}).$$

Imply,

$$\frac{\Theta_{OPT}}{\Theta_{NE}} \leq \frac{\sum_{i=k+1}^{n} \lambda_i (1 \quad f(r_i))}{\sum_{i=k+1}^{n} \lambda_i \left(1 - f\left(\frac{1}{n\lambda_i}\right)\right)}$$

$$\leq \frac{\sum_{i=k+1}^{n} \lambda_i f(r_i)}{\sum_{i=k+1}^{n} \lambda_i f\left(\frac{1}{n\lambda_i}\right)}$$

$$\leq \frac{\sum_{i=k+1}^{n} \lambda_i f(r_i)}{\sum_{i=k+1}^{n} \lambda_i f\left(\frac{1}{n\lambda_{k+1}}\right)} \quad \textit{because } \lambda_{k+1} \leq \lambda_{k+2} \leq \dots \leq \lambda_n$$

$$\leq \frac{f(r_i)}{f(\frac{1}{n\lambda_{k+1}})} = \frac{f(\frac{1}{\sum_i \lambda_i})}{f(\frac{1}{n\lambda_{k+1}})}$$

$$\leq \frac{\sum_i \lambda_i}{n\lambda_{k+1}}.$$

The last inequation holds because the cost function *f* is a convex function and reversely proportional to the input relative rate. In this case, the linear cost function will cause the worst result. This ratio is maximum when $\lambda_{k+1} \simeq \lambda_1$ and $\lambda_{k+2} = \dots = \lambda_n$, means,

$$\frac{\Theta_{OPT}}{\Theta_{NE}} \leq \frac{\lambda_2}{\lambda_1}.$$

5. CONCLUSION

In this paper, we study the reservation-based bandwidth sharing protocols considering selfish stations. A deep insight into this non-cooperation system is presented through game-theoretic aspects. We show the existence and convergence of the Nash equilibrium as well as the bound on the price of anarchy. Analysis shows that the optimal bandwidth sharing scheme for the cooperation case is not efficient in the non-cooperation case. In the worst case, the system throughput is quite far from that of the optimal solution. Therefore, non-cooperative systems necessarily need a new treatment.

In our work, we assume that stations treat their data as the same priority at any timeframe. However, if the priority of data is different by the time, i.e. stations' references are varied by the time, this issue merits for further research. Finally, we are still far from the situations where stations have different goals.

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