Cooperation and Fairness for Slotted Aloha

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Abstract. Wireless access based on slotted Aloha with selfish users may result in very inefficient use of the system resources. To impose cooperation and fairness in such systems, we propose an optimal pricing strategy, based on which the service provider can regulate the overall network behavior. As the users' utility incorporates the price paid for using the spectrum, by striving to improve their own performance, the users act to optimize the overall network performance. Our analysis is based on a game theoretic framework, and we consider both the simple collision model for packet reception, as well as multipacket reception capabilities for the physical layer. The proposed pricing strategy enforces fairness under the constraint of an equal access probability.

Keywords: Aloha, Game theory, Cooperation, Fairness

1. Introduction

Medium Access Control (MAC) is central to the successful deployment of modern wireless networks, where users are expected to manage resources in a decentralized fashion [1], [2], [3]. In this context, a recent focus in MAC protocol design has been on the behavior of access control protocols in the presence of selfish users that seek to maximize their own performance. At a first glance, it may seem that selfish users running their own MAC strategies could lead to protocol failures by constantly colliding in an attempt to maximize their individual throughput. The results in [4] have contradicted this hypothesis and have showed that a distributed Aloha based MAC protocol for selfish users is viable and stable. However, the obtained throughput for the system analyzed in [4] is lower than that of a centrally controlled Aloha, and depends on the cost associated with the users' transmissions. The results in [4] motivate our current research, which seeks to improve the selfish users' Aloha throughput by introducing a differentiated fair pricing mechanism. In essence, this pricing mechanism enforces cooperation among users, with the goal of optimizing the overall network performance.

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In this paper, we show that by enforcing cooperation through pricing mechanisms, the throughput of the centralized slotted Aloha can be achieved in a network in which selfish users access the network attempting to maximize their own utility.

Game theoretic formulations for analyzing MAC protocols [5],[6], and in particular slotted Aloha, were recently proposed in the literature, including the work in [4], its extension for multipacket reception models in [7], and a pricing strategy in [8] for an Aloha network of heterogeneous users with inelastic bandwidth requirements. The game model in [5] and [6] assigns different transmission probability for retransmitted and new packets, and uses a Markov chain to obtain the optimum throughput. The game model in [8] constructs a concave utility function for the price the users are willing to pay and the throughput they want to get, associated with the charge of the network. Consequently, the network can achieve a required throughput using this pricing strategy. However, the work in [5], [6] and [8] does not model the transmission cost of each transmission, such as the energy consumption associated with packet transmission. Another shortcoming of the model considered in [5], [6] and [8] is that all the users are assumed to be willing to pay the same price to the network and the network charges are the same for all the users, irrespective of their channel quality or energy consumption. Also, multipacket reception capability for the channels is not considered in [5], [6] and [8].

In this paper, we extend the work in [4] and [7] to allow for a more realistic model in which users have differentiated transmission costs for packet transmissions (e.g., energy consumption based on channel quality), and their utilities are affected by this transmission cost, as well as the delay experienced due to the access control. Furthermore, to enforce fairness and cooperation, we introduce a pricing strategy which maximizes the system performance. We consider two different optimization criteria: throughput and revenue maximization. We further extend our model to consider improvements at the physical layer that will allow for multipacket reception.

The paper is organized as follows. In section 2, a game theoretic formulation for slotted Aloha with energy constraints is proposed. The analysis of the Nash equilibrium for slotted Aloha with a collision model is presented in section 3, while multipacket reception is analyzed in section 4. Conclusions are presented in section 5.

2. Game model for slotted Aloha with pricing

In this section, we present a game-theoretic model for slotted Aloha. Each slot of the system is a one-stage game. At the beginning of each slot, the players learn the current state of the game, which is the number of users (N) who currently have packets to send. Each of these players has two possible actions: transmit (T) or wait (W). When a user transmits, its transmission can either succeed (S), or fail (F). The gain associated with a successful transmission is a normalized throughput of 1, while the cost of transmitting for user i is c_i (e.g., energy cost), and the network's current charge for this user is μ_i. In our game, different nodes can have different transmission costs. If player i transmits and succeeds in a given slot, then that player will receive a payoff of $1 - c_i - \mu_i$ for that slot (throughput - energy cost - price paid). If the user refrains from transmission in a particular slot (waits), this will result in one slot delay for that user. This delay is associated with the loss in the throughput the player could have achieved if it transmitted and succeeded. Thus, the payoff for this waiting user i can be determined as $-(1 - c_i - \mu_i)$ (the negative of the gain it could have been achieved if successful). Note that this cost strategy corresponds to users that are aggressively using the system resources. They value an opportunity to send, such that they believe that if they would have sent, they would have been successful in their transmission. For that reason, the waiting cost for these users is only associated with the successful throughput. However, if player i transmits but fails, it will incur a transmission cost c_i as well as one slot delay, but it will not pay for the transmission (we assume that a user is charged only for successful transmissions). Therefore, the payoff of this player in this case can be defined as $-(1 - c_i - \mu_i) - c_i = -1 + \mu_i$. Each player's goal is to maximize its own payoff. The payoff function for player i is summarized in table I.

Table I. Payoff functions

T and S	T but F	W
$1 - c_i - \mu_i$	$-1 + \mu_i$	$-(1 - c_i - \mu_i)$

In this paper, we focus on a fair pricing strategy, i.e., all the users must use the same transmission probability. Our approach to optimize the system performance is to appropriately select the prices μ_j, $j = 1, \ ,\cdots, \ N$, for all the users, according to their transmission costs c_j,

$j = 1, \ , \cdots , \ N$, in order to achieve an optimal transmission probability p.

3. Equilibria for the collision model

In this section, we consider the case of the classical collision model, for which a transmission is considered to be successful only when a single user transmits, and we study the equilibrium point for the slotted Aloha game defined in the previous section. The above defined game is a finite strategic-form game, and thus we know (Theorem 1.1 in [9]) that a mixed strategy equilibrium for the game exists.

In the game described in the above section, every player has two strategies, transmit (T) or wait (W). A mixed strategy equilibrium for this game will essentially represent the equilibrium transmission probability, from which no player has incentive to deviate. This can be determined using the indifference principle: a player must be indifferent between all the pure strategies to which he assigns a positive probability.

The payoff that player i can get from selecting action T is

$$v(T, i) = (-1 + \mu_i) \left[1 - (1 - p)^{N-1}\right] + (1 - c_i - \mu_i)(1 - p)^{N-1}. \quad (1)$$

The payoff that player i gets with action W is

$$v(W, i) = -(1 - c_i - \mu_i). \quad (2)$$

Consequently, to obtain the nondegenerate equilibrium strategy for the proposed Aloha game, we use the indifference principle, i.e. the payoffs for transmission and waiting should be the same:

$$v(T, i) = v(W, i). \quad (3)$$

Thus, the mixed Nash equilibrium transmission probability p, can be determined as

$$p = 1 - \sqrt[N-1]{c_i/(2 - 2\mu_i - c_i)}. \quad (4)$$

We can see that the transmission probability not only depends on the transmission cost c_i, but also on the price charged by the network, μ_i. In turn, the transmission probability will influence the achievable network throughput at the equilibrium point, and in combination with the pricing scheme, the revenue of the network provider.

Consequently, we can optimize the pricing scheme, given the two above mentioned criteria: throughput and revenue.

3.1. Throughput optimization

In this subsection, we address the problem of throughput maximization. The network adjusts pricing according to different transmission costs in order to achieve the maximum throughput. It is well known that the network throughput S of a centrally controlled system is $Np(1-p)^{N-1}$ [12], and the maximum throughput is achieved when $p = 1/N$. Therefore, from (4) and $p = 1/N$, the optimal pricing to maximize the throughput is,

$$\mu_i = 1 - \frac{(1-1/N)^{N-1}+1}{2(1-1/N)^{N-1}} c_i. \tag{5}$$

From (5), it can be seen that even though different players have different transmission costs, the network throughput can be maximized by charging them differently. The price μ_i is monotonically decreasing with the increase in the transmission cost c_i. This result is intuitively appealing, since the network should reduce its charging price to encourage users to transmit when their transmission costs are high. When N is very large, $lim_{N\to\infty}(1-1/N)^{N-1} = 1/e$, and (5) becomes

$$\mu_i = 1 - \frac{1+e}{2} c_i. \tag{6}$$

Figure 1 gives the relation between c_i and μ_i when N is very large. We note that all costs and benefits in the utility function, are normalized to 1. In particular we can think of c_i in terms of the fraction of the total battery energy level. The current transmission is going to require $c_i = E_i(packet)/E_i$, $E_i(packet)$ is the energy player i consumes to transmit the current packet and E_i is the total battery energy of user i. Since we expect that the energy spent for the current packet transmission should be much less than the total energy level of the battery for the user, for illustration purposes, we have selected a range for c_i in between 0 and 0.1.

3.2. Revenue optimization

In the above subsection, the network decides the price charging for different users aiming to maximize the throughput of the whole network. In this subsection, we consider a more practical objective for the service provider which is to maximize revenue. Assuming that the network charges only for successful transmission and that a fair policy is enforced, for which all users have the same transmission probability p, the amount of service provided by the network to each user can be determined to be $p(1-p)^{N-1}$. Consequently, the revenue for the

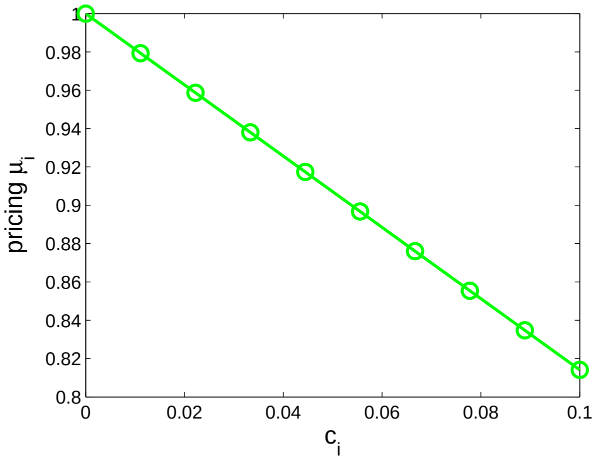

Figure 1. Pricing and transmission cost

network is given by

$$\rho = \sum_{i=1}^{N} \mu_i p(1-p)^{N-1}. \tag{7}$$

Since user i and user j have the same transmission probabilities, then, given (4), we have

$$1 - \sqrt[N-1]{c_i/(2-2\mu_i - c_i)} = 1 - \sqrt[N-1]{c_j/(2-2\mu_j - c_j)}. \tag{8}$$

Thus,

$$\mu_i = \frac{c_i}{c_j}(\mu_j - 1) + 1. \tag{9}$$

Since $2 - 2\mu_i - c_i > 0$, and $c_i > 0 \to \mu_j < 1$, it can be seen from (9) that the larger the transmission costs, the lower the pricing. Without loss of generality, we select user 1 as the reference. Then, the revenue of the network can be computed as

$$\rho = \sum_{i=1}^{N} \left[\frac{c_i}{c_1}(\mu_1 - 1) + 1\right] \times \left[p(1-p)^{N-1}\right]. \tag{10}$$

From (4), we can also get

$$\mu_1 = 1 - \frac{c_1}{2} - \frac{c_1}{2(1-p)^{N-1}}. \tag{11}$$

Let $c = \sum_{i=1}^{N} c_i$, and substitute (11) into (10). Then,

$$\rho = (N - \frac{c}{2})p(1-p)^{N-1} - \frac{c}{2}p. \tag{12}$$

To achieve the maximum revenue,

$$\frac{\partial \rho}{\partial p} = (N - \frac{c}{2})(1-p)^{N-2}(1-Np) - \frac{c}{2} = 0. \tag{13}$$

Since $0 < c_i < 0.1$, $N - \frac{c}{2} > \frac{c}{2}$, there must exist a p satisfying (13). However, it is not easy to solve for an exact solution to (13). As $\lim_{N\to\infty}(1-p)^{N-2} = 1-(N-2)p$, we can get an approximate solution:

$$p = \frac{2N-2-\sqrt{(-2N+2)^2 - 4N(N-2)(1-\frac{c/2}{N-c/2})}}{2N(N-2)}. \tag{14}$$

In Figures 2, 3 and 4, we compare the transmission probabilities, the revenue and the throughput obtained for the two considered optimization metrics (throughput and revenue). For all simulations, the selected number of users N is 100. It can be seen from Figure 2 that for the case of revenue optimization, the transmission probability decreases with the increase in the transmission costs. For throughput optimization, the transmission probability remains constant, irrespective of the transmission costs and the maximum throughput is uniquely decided by the optimal transmission probability which does not change with the transmission costs. The network charges the users according to the their transmission costs in order to achieve an optimal transmission probability.

For the revenue optimization, the revenue of the network is decided by the pricing and the transmission probabilities. The optimal transmission probability changes with the transmission costs (sum of the costs for all the users). Since higher transmission costs mean lower charges, the effect of the pricing optimization is to reduce the transmission probabilities when the transmission costs are high. In Figure 3, it can be seen that very similar revenues are obtained by the network provider for both optimization metrics, for a cost range of $c_i \in [0,\ 0.1]$. However, Figure 4 shows a much better throughput if the pricing scheme is optimized to maximize the network throughput, compared to the revenue maximization case. Thus, it seems that for the given range of the transmission costs, $c_i \in [0,\ 0.1]$, a better overall network performance for both users and the service provider can be achieved by optimizing the network throughput. The achievable throughput is the same as that of a centrally controlled slotted Aloha (without accounting for transmission costs).

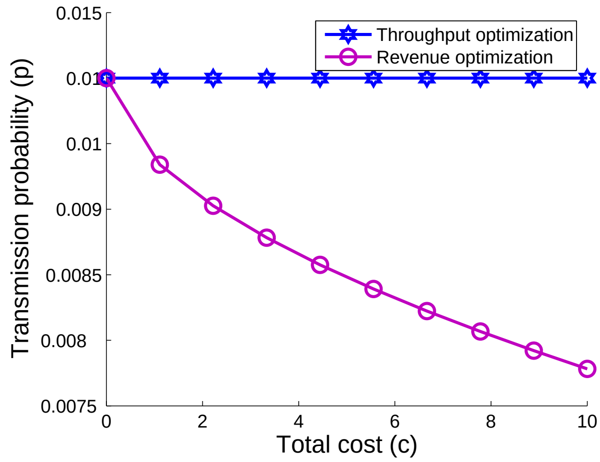

Figure 2. Optimal transmit probability: collision model

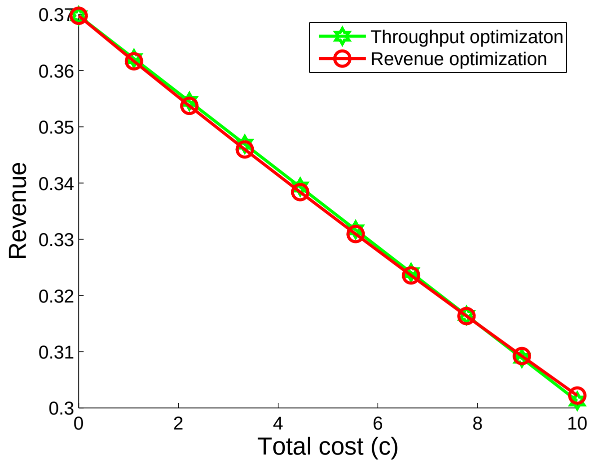

Figure 3. Revenue comparison: collision model

4. Equilibria for the multipacket reception model

In the previous section, we have analyzed the fundamental collision model, for which two packets simultaneously transmitted always collide and are assumed lost.

However, enhancements at the physical layer (e.g., beamforming, MIMO systems, multiuser detection, etc.) result in multipacket reception (MPR) capabilities, i.e., more packets may be successfully received simultaneously. In this section, we use the game model presented in

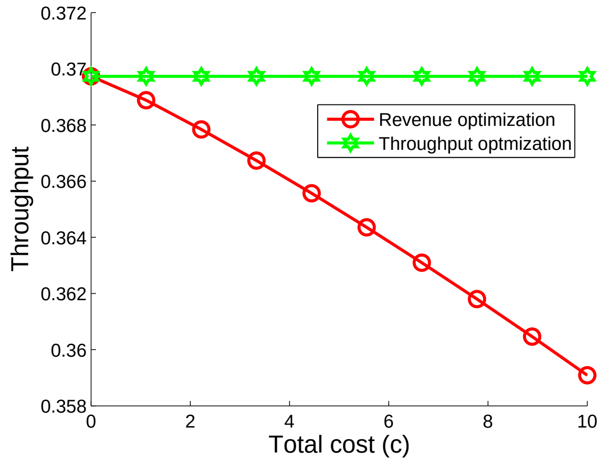

Figure 4. Throughput comparison: collision models

section II to analyze the equilibrium point of slotted Aloha for MPR channels. We have adopted the analysis model in [7] and [10]. The channel is described by an MPR matrix:

$$R = \begin{bmatrix} \rho_{10} & \rho_{11} & 0 & 0 & \cdots & 0 & \cdots \\ \rho_{20} & \rho_{21} & \rho_{22} & 0 & \cdots & 0 & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \rho_{n0} & \rho_{n1} & \rho_{n2} & \cdots & \rho_{nn} & 0 & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \end{bmatrix}, \tag{15}$$

where ρ_{nl} denotes the probability that l packets are successfully received in a slot where n packets are transmitted. Similar to [7], the expected number of successes in a transmission of size n is given by

$$r_n = \sum_{l=0}^{n} l\rho_{nl}. \tag{16}$$

Let $b_p(n,k) = \begin{pmatrix} n \\ k \end{pmatrix} p^k(1-p)^{n-k}$ be the probability of k packets out of n transmitted, where p is equilibrium transmission probability for all the players. Similar to the Aloha game for the collision model, a mixed Nash equilibrium exists for this finite strategy form game. We derive the equilibrium strategy in a similar fashion as before. The payoff for transmission is

$$v(T,i) = (1 - c_i - \mu_i)\left[\sum_{k=1}^{N} b_p(N-1,k-1)\frac{r_k}{k}\right] + (-1+\mu_i)\left[1 - \sum_{k=1}^{N} b_p(N-1,k-1)\frac{r_k}{k}\right]. \tag{17}$$

The payoff for waiting is

$$v(W,i) = -(1 - c_i - \mu_i). \tag{18}$$

From $v(T,i) = v(W,i)$, we can obtain

$$\sum_{k=1}^{N} b_p(N-1,k-1)\frac{r_k}{k} = \frac{c_i}{2 - 2\mu_i - c_i}. \tag{19}$$

The mixed Nash equilibrium is the solution of (19). When N is very large and p is very small, let $\gamma = lim_{N\to\infty} Np$, and Poisson approximation to (19) yields

$$\sum_{k=1}^{\infty} \frac{e^{-\gamma}\gamma^{k-1} r_k}{k!} = \frac{c_i}{2 - 2\mu_i - c_i}. \tag{20}$$

The solution of (20) is denoted as $\hat{\gamma}$. Therefore, for all users, the Nash equilibrium is

$$p = \hat{\gamma}/N. \tag{21}$$

According to [7], the system is stable if

$$\lambda < e^{-\hat{\gamma}} \sum_{k=1}^{\infty} \frac{\hat{\gamma}^k}{k!} r_k, \tag{22}$$

where λ is the arriving rate of the selfish users. As for the centrally controlled Aloha case, the authors in [10] showed stability if

$$\lambda < sup_{x\geq 0} e^{-x} \sum_{k=1}^{\infty} r_k x^k / k!. \tag{23}$$

If there is a value of $x > 0$ achieving this sup, then there exists a $\hat{\gamma} = x$. Since $\hat{\gamma}$ depends on the transmission cost c_i and pricing μ_i, according to different c_i, the network can adjust this pricing μ_i to make $\hat{\gamma} = x$. Therefore, there must exist an optimal transmission probability which makes the system stable and gets the maximum throughput.

In the following, we use the capture model in [10] to investigate the effect of pricing on the random access protocol. The MPR matrix can be redefined as:

$$R = \begin{bmatrix} 0 & 1 & 0 & 0 & \cdots & 0 & \cdots \\ 1-1/\beta^2 & 1/\beta^2 & 0 & 0 & \cdots & 0 & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 1-1/\beta^2 & 1/\beta^2 & 0 & \cdots & 0 & 0 & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \end{bmatrix}, \tag{24}$$

where $r_1 = 1$ and $r_k = 1/\beta^2$ for $k \neq 1$. β is a measure of the packet capture capability of the system, such that smaller β denotes a stronger capture capability.

In what follows, we optimize the network pricing strategy according to the same two criteria previously discussed: throughput and revenue maximization.

4.1. Throughput optimization

In this subsection, we use throughput optimization as a metric. From (23), we know that the optimal throughput given pricing μ_i and transmission cost c_i is

$$s = e^{-\hat{\gamma}} \sum_{k=1}^{\infty} \frac{\hat{\gamma}^k}{k!} r_k \tag{25}$$

where $\hat{\gamma}$ is the solution of (20). Now the problem reduces to determine μ_i and $\hat{\gamma}$. Let $\alpha_i = \frac{c_i}{2-2\mu_i-c_i}$, then (20) becomes

$$\sum_{k=1}^{\infty} \frac{e^{-\hat{\gamma}}\hat{\gamma}^k r_k}{k!} = \hat{\gamma}\alpha_i. \tag{26}$$

Therefore, the optimal throughput s in (25) is denoted as

$$s = \alpha_i \hat{\gamma}. \tag{27}$$

Since the maximum throughput under optimal control is $1/\beta^2 + (1 - 1/\beta^2)e^{(-\beta^2/(\beta^2-1))}$ [11], and the target of the network is to adjust the pricing to get the maximum throughput, then

$$\alpha_i \hat{\gamma} = 1/\beta^2 + (1 - 1/\beta^2)e^{(-\beta^2/(\beta^2-1))}. \tag{28}$$

By substituting $r_1 = 1$ and $r_k = 1/\beta^2$ for $k \neq 1$ into (26), we get

$$e^{-\hat{\gamma}}(\beta^2\hat{\gamma} - 1 - \hat{\gamma}) = \alpha_i \beta^2 \hat{\gamma} - 1. \tag{29}$$

From (28) and (29), we determine

$$e^{-\hat{\gamma}}(\beta^2\hat{\gamma} - 1 - \hat{\gamma}) = (\beta^2 - 1)e^{-\beta^2/(\beta^2-1)}. \tag{30}$$

It can be seen that $\hat{\gamma} = \frac{\beta^2}{\beta^2-1}$ is the solution of (30). Then,

$$\alpha_i = \frac{\beta^2 - 1}{\beta^4} + \frac{(\beta^2-1)^2}{\beta^4} e^{-\frac{\beta^2}{\beta^2-1}}, \tag{31}$$

and

$$\mu_i = \frac{2\alpha_i - \alpha_i c_i - c_i}{2\alpha_i} = 1 - \frac{c_i}{2} - \frac{c_i}{2\alpha_i}. \tag{32}$$

Figure 5 illustrates the relationship between the capture parameter β^2 and α_i. Although α_i plays a similar role with the optimal transmission costs in [7] where the transmission costs are predetermined, α_i here depends on the network pricing policy, and can be optimized to maximize the network throughput.

Figure 6 gives the relationship between the capture parameter β^2 and the pricing μ_i. Similar to the simple collision model case, the prices decrease with the increase of the transmission costs. We can also see that, for a given transmission cost, the smaller the capture parameter, the lower the network charge. This is due to the fact that a smaller capture parameter yields stronger capture capability for the MPR system, and results in the network encouraging users to transmit with a higher probability.

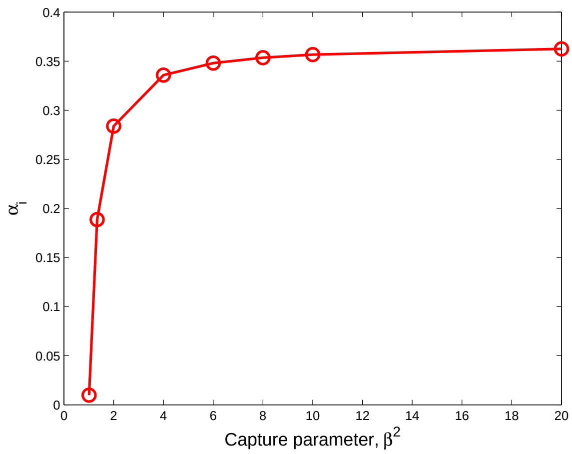

Figure 5. α_i and capture parameter

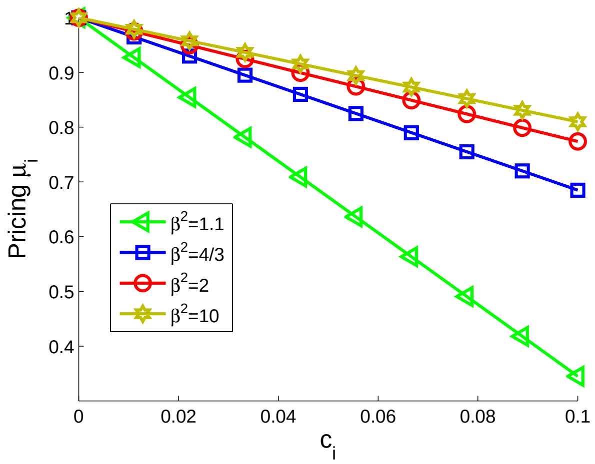

Figure 6. Pricing and transmission cost with different capture parameter

4.2. Revenue optimization

We analyze now how to select a pricing policy that maximizes revenue for the service provider. For N users in the system, the amount of service provided by the network to each user is $p\sum_{k=1}^{N}\left[b_p(N-1,k-1)\frac{r_k}{k}\right]$. Therefore, the revenue of the network is

$$R=\sum_{i=1}^{N}\mu_i p\left(\sum_{k=1}^{N}\left[b_p(N-1,k-1)\frac{r_k}{k}\right]\right). \tag{33}$$

When N is very large and p is very small, from (19), (20), and (33) the network revenue can be determined as

$$R=\sum_{i=1}^{N}\mu_i p\alpha_i. \tag{34}$$

By substituting $r_1=1$ and $r_k=1/\beta^2$ for $k\neq 1$ into (20), we get

$$\alpha_i=\frac{c_i}{2-2\mu_i-c_i}=\frac{e^{-\hat{\gamma}}(\beta^2\hat{\gamma}-\hat{\gamma}-1)+1}{\beta^2\hat{\gamma}}, \tag{35}$$

and

$$\mu_1=1-\frac{c_1}{2}-\frac{c_1\beta^2\hat{\gamma}}{2\left[e^{-\hat{\gamma}}(\beta^2\hat{\gamma}-1-\hat{\gamma})+1\right]} \tag{36}$$

.

Similar to the collision model case, the same relation for μ_i as in (9) can be obtained from (20). Thus, substituting (35), (36) and (9) into

(34), we get

$$R = \frac{1}{\beta^2}(1 - \frac{c}{2N}) \left[e^{-\hat{\gamma}}(\beta^2 \hat{\gamma} - 1 - \hat{\gamma}) + 1 \right] - \frac{c}{2N}\hat{\gamma}, \tag{37}$$

where, $c = \sum_{i=1}^{N} c_i$.

The maximum revenue can be obtained by setting the revenue derivative to zero

$$\frac{\partial R}{\partial \hat{\gamma}} = \frac{1}{\beta^2}(1 - \frac{c}{2N})e^{-\hat{\gamma}} \left(\beta^2 - \beta^2 \hat{\gamma} + \hat{\gamma} \right) - \frac{c}{2N} = 0. \tag{38}$$

It is not easy to get the exact solution of (38). We can get numerical solutions as in Figure 7. From Figure 7, we can get the optimal transmission probability, throughput and revenue shown in Figures 8, 9 and 10 for the two considered optimization metrics. It can be seen that smaller βs which denote stronger capture capability usually yield higher transmission probability, throughput and revenue. As in the collision model case, when the transmission cost is very large, the optimal transmission probability becomes very small for the revenue optimization scenario. However the throughput and revenue optimization no longer give identical revenue for the service provider and there is a trade-off between throughput optimization and revenue optimization.

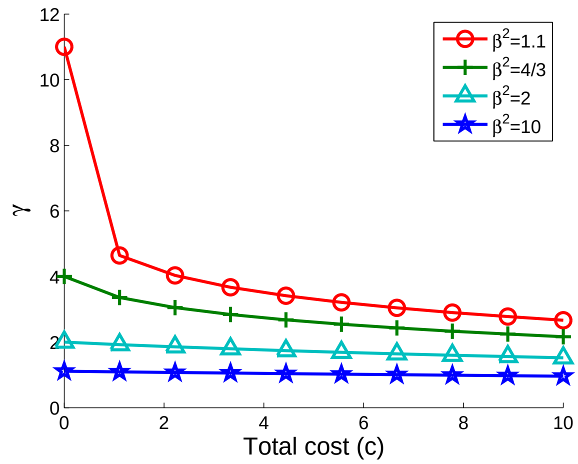

Figure 7. γ and transmission cost

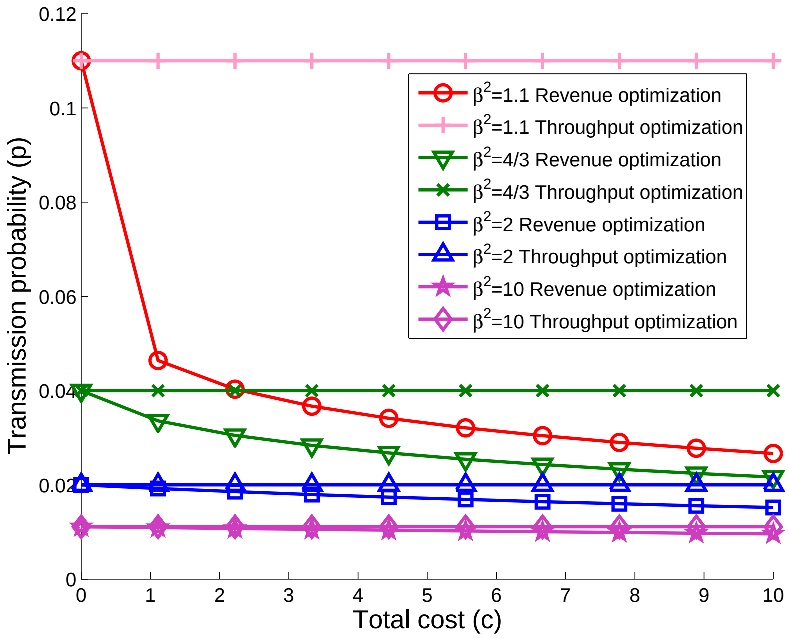

Figure 8. Optimal transmission probability: MPR model

5. Conclusion

In this paper, we have studied the problem of enforcing cooperation and fairness for selfish users in slotted Aloha, for both collision and multipacket reception models. We have showed that, if the users' utility is modified to account for network pricing, no performance loss is incurred in the overall network performance, because of users' selfishness. We have considered as performance metrics the network throughput and the revenue for the service provider. Our analysis is based on a game theoretic framework. Our results prove the viability of distributed MAC implementation in networks with selfish users, and determine the required policy to enforce cooperation and fairness in such networks, in order to optimize the overall network performance.

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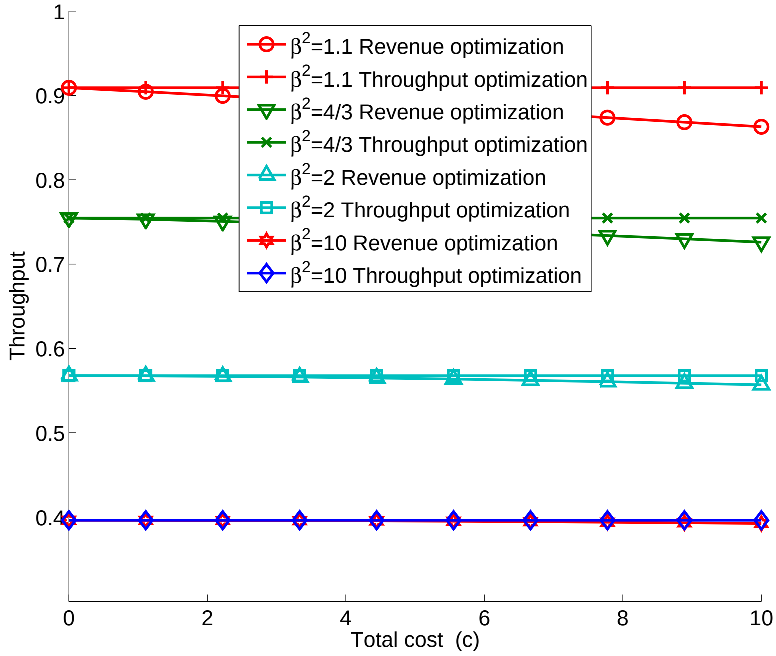

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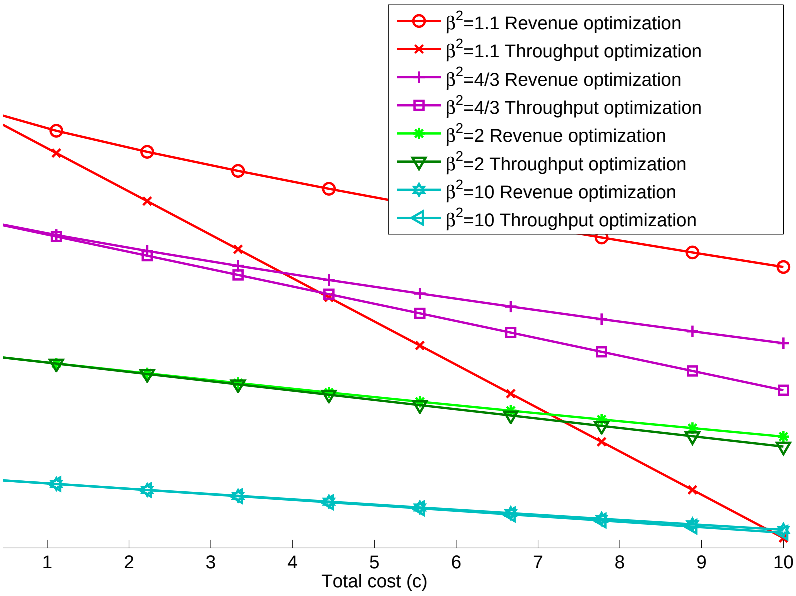

Figure 10. Revenue: MPR model

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