Facilitating Incentive-Compatible Access Probability Selection in Wireless Random Access Networks

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SUMMARY This paper studies the impact of integrating pricing with connection admission control (CAC) on the congestion management practices in contention-based wireless random access networks. Notably, when the network is free of charge, each self-interested user tries to occupy the channel as much as possible, resulting in the inefficient utilization of network resources. Pricing is therefore adopted as an incentive mechanism to encourage users to choose their access probabilities considering the real-time network congestion level. A Stackelberg leader-follower game is formulated to analyze the competitive interaction between the service provider and the users. In particular, each user chooses the access probability that optimizes its payoff, while the self-interested service provider decides whether to admit or to reject the user’s connection request in order to optimize its revenue. The stability of the Stackelberg leader-follower game in terms of convergence to the Nash equilibrium is established. The proposed CAC scheme is completely distributed and can be implemented by individual access points using only local information. Compared to the existing schemes, the proposed scheme achieves higher revenue gain, higher user payoff, and higher QoS performance.

key words: CAC, Stackelberg game, backward induction, pricing, wireless random access network

1. Introduction

We consider a wireless random access network that adopts a slotted-Aloha like MAC protocol [1]. Such a protocol provides non-coordination and lets users contend for channel access arbitrarily. When multiple users simultaneously send packets in a slot, their packets collide and have to be dropped. The dropped packets must be retransmitted later. A key feature of the random access network is that the Quality of Service (QoS) may degrade dramatically if the traffic admitted into the network exceeds the channel capacity [2].

From the perspective of engineering, the purpose of connection admission control (CAC) is to limit the amount of traffic admitted into the networks so that the QoS of existing users will not be degraded dramatically. From the perspective of economics, an incoming user means a potential gain to the network revenue due to the improved utilization of network resources; on the other hand, the incoming user may cause congestion and QoS degradation to existing users. In commercial networks, in case that the utility decreases below the price charged, existing users may quit, which in turn results in a loss to the network revenue. Therefore, CAC should play an important role in both the QoS provisioning and the revenue optimization [3].

Furthermore, in contention-based wireless networks, users always act selfishly without considering the overall resource utilization and performance. As studied in [1], if each user tries to occupy the channel as much as possible, the overall saturation throughput decreases dramatically. Incentive mechanisms are hence essential for users to voluntarily cooperate with each other to improve the overall resource utilization and performance. This can be efficiently achieved through pricing [4] in commercial networks.

In this paper, we first investigate the case that the network is free of charge, and show that every user hence tries to occupy the channel as much as possible, resulting in an inefficient utilization of network resources. A simple pricing scheme is therefore adopted as incentive mechanism that encourages users to choose their access probabilities considering the real-time network congestion level.

A Stackelberg leader-follower game [5] is a strategic game in which a leader player commits to a strategy first and then other followers move sequentially. Furthermore, Nash equilibrium [5] is a profile of strategies such that no player in the game can improve its payoff by changing its own strategy unilaterally. In other words, each player is doing the best response to the others’.

In this paper, a Stackelberg leader-follower game [5] is formulated to analyze the interaction between the service provider and the users. In particular, each user chooses the access probability that optimizes its payoff, while the service provider decides whether to admit or to reject the user’s connection request to optimize its revenue. The stability of the Stackelberg leader-follower game in terms of convergence to the Nash equilibrium is established. The proposed CAC scheme is completely distributed and can be implemented by individual access points (APs) using only local information.

The remainder of this paper is organized as follows. Section 2 gives an overview of existing work related to
the problem that we are addressing. Section 3 introduces the system model. Section 4 describes the users’ behaviour when the wireless random access network is free of charge and proves that the network can be easily overtaken without a proper pricing scheme, and presents the access-probability-based pricing scheme. Section 5 describes the Stackelberg leader-follower game modelling structure, and investigates the condition under which the Stackelberg leader-follower game converges to an equilibrium solution. Section 6 presents the sequence of steps involved in QoS negotiation and admission control, which gives an overview of the proposed algorithm. Section 7 shows the simulation results. Finally, Sect. 8 concludes this paper.

2. Related Work

Economic aspects of network resource allocation have drawn much attention in recent years. In [6], the authors investigated economic behaviour of users in a wireless network with a limited capacity. The authors then devised an optimal pricing strategy under an assumption that each AP is limited to admit at most $m$ users at a time. This is a strong assumption since, in a real network, if the admission of the $\text{"}m+1\text{"}-\text{th}$ user can increase its overall revenue, a rational service provider will not reject the new connection request.

In [7], the authors derived the maximum number of connection requests that can be admitted in a wireless network by solving a revenue optimization problem. Then the maximum number is used as a threshold value to admit or to reject connection requests. In [8], [9], the authors tried to obtain user information from surveys, and proposed CAC schemes for maximizing the network revenue as well as the users’ payoffs. However, the above mentioned approaches either assume that there is no competition among users or require that the service provider has a global knowledge of each user’s utility function, which is not realistic.

When conflicting interests exist among interacting decision makers, game theory is regarded as a powerful tool to model the competition. As well surveyed in [10], game theory has been used in a variety of optimization purposes in wireless networks, such as, admission control, revenue optimization, load balancing, etc. [11]–[16].

In [11], a Stackelberg game is constructed to analyze ALOHA networks, where two self-interested nodes, i.e., a leader node and a follower node, compete for bandwidth with each other. The game finally benefits the leader node by sacrificing the throughput of the follower node.

The work in [12], on the other hand, focuses on price competition among service providers. The authors considered the case where a service provider can offer its price before other providers. A Stackelberg game is then employed to model the interaction between a leader service provider and other follower providers. The Nash equilibrium is employed as the pricing solution. In [13], a network selection scheme is modelled as a game between two non-cooperative WiMAX networks. The networks compete with each other in order to maximize their revenue by accepting the connection requests with higher network utility.

Nevertheless, none of the games formulated in [11]–[13] attempts to capture the interaction between the service provider and wireless users, nor do they aim at maximizing the service provider’s revenue while at the same time providing wireless users with incentive to efficiently utilize network resources.

A primary model that involves the participation of both service provider and wireless users is first introduced in [14]. The study considers economic aspects of services deployment by providers as well as provider selection by users in a competitive environment. This is further studied in [15] by formulating a game to capture the competitive interaction between the service provider and the users. The service provider can decide whether to admit or to reject the users’ connection request and the users can switch their providers freely. In [16], user’s subscription to a provider is performed on a session basis. The authors studied how session admission control integrated with pricing can affect the competitiveness of providers.

The scenario considered in this paper differs from those in [14]–[16] in the following aspects:

- switching cost, which prevents users from changing their contracted service providers freely, is not negligible;
- network resource is limited, and users compete with each other in sharing the limited resource.

Since it is the service provider that has the priority to determine the price as well as whether to admit or to reject the incoming users’ connection request, a Stackelberg leader-follower game is naturally employed to model the interaction between the service provider and the users. Specifically, the service provider is the leader that decides the price as well as whether to admit or to reject the users’ connection request. The users are the followers that can choose their access probabilities by considering the real-time network congestion level.

In this paper, we try to satisfy the three challenges: QoS provisioning, revenue optimization and incentive compatibility simultaneously to provide a sustainable network with integrated services [17]. To the best of our knowledge, this is the first work that addresses the above-mentioned three challenges simultaneously in a contention-based wireless random access networks.

3. System Model

Time is divided into slots. Each node can attempt to send one packet in each slot. We consider a wireless random access network that adopts a slotted-Aloha like MAC protocol. Such a protocol provides non-coordination by letting users contend for channel access arbitrarily. As shown in Fig. 1, when multiple users transmit packets simultaneously, their packets collide and have to be dropped. The dropped packets must be retransmitted later.

We assume that users contend for channel access ac-
According to the user-chosen access probabilities. QoS differentiation is achieved in such a way that users with high access probabilities transmit more often than those with low access probabilities [18]. For window-based protocols such as IEEE 802.11, changing access probability can be implemented by adjusting window size [19]. Therefore, the analysis and related results here can be extended to such scenarios easily.

The number of existing users is denoted by \( n \), and the access probabilities chosen by the existing users are denoted by \( x_i, i \in \{1, \ldots, n\} \). Moreover, let \( x \) be the access probability chosen by the incoming user. Since a transmission is successful if and only if there is a single transmission attempt at that time, the saturation throughput (rate of success) of the incoming user is given by \( \tau \) as follows.

\[
\tau = x \prod_{i=1}^{n} (1 - x_i)
\]  

(1)

User demand is assumed to be elastic [20], [21], and the utility of the incoming user is given by \( U \) as shown in Eq. (2).

\[
U = \alpha + \theta \ln(1 + \tau)
\]  

(2)

where \( \alpha \) is a positive constant and \( \theta \) is a user-dependent scale factor and can be thought of as a parameter representing the priority of the incoming user’s willingness to pay (WTP). Traditional data applications (e.g., e-mail, web browsing, file transfer, or software update) are elastic, in that they incline to be tolerant of variations in delay, and can work with even minimal amounts of bandwidth.

A summary of the main notations used throughout the paper is given in Table 1.

4. Access-Probability-Based Pricing

When the network is free of charge, the payoff for the incoming user is given by \( F(x) \) as follows.

\[
F(x) = \alpha + \theta \ln \left[ 1 + x \prod_{i=1}^{n} (1 - x_i) \right]
\]  

(3)

Consider the following primal optimization problem

\[
\begin{align*}
\text{maximize} & \quad F(x) \\
\text{subject to} & \quad 0 \leq x \leq \beta
\end{align*}
\]  

(4)

(5)

where \( \beta \in (0, 1) \) is the maximum access probability that a user can choose.

Since \( F(x) \) is continuous and strict increasing function for \( x \), it can therefore be concluded that, at a maximum of \( F(x) \) over \( 0 \leq x \leq \beta \), the following condition holds.

\[
x = \beta
\]  

(6)

Namely, no matter what access probabilities \( \{x_i, i = \{1, \ldots, n\}\} \) that other users choose, selecting an access probability that equals to the upper bound value \( \beta \) is always a dominant strategy [5] for the incoming user. Since all the users are symmetric, and therefore try their best to occupy the channel as much as possible. As a consequence, the network can be easily overtaken by the self-interested users [22].

To address the above-mentioned problem, pricing is adopted to dynamically regulate network traffic by exploiting the elasticity of demand with respect to price [23].

We assume that each user pays a price per unit time that is proportional to the access probability. Namely, the price per unit time is set to \( px \) for the incoming user, and \( px_i \) for the existing users \( i \in \{1, \ldots, n\} \), where the rate of charge \( p \) is a constant.

The service provider can decide whether to admit or to reject the user’s connection request at the very beginning. However, during the session of service, the service provider cannot suspend the service as long as the user can keep paying; while the user can disconnect voluntarily. The service session ends at the first time the user rejects the service provider’s price proposal, including the following cases:

- the user realizes that the price is too high to accept

\begin{table}[h]
\centering
\caption{A summary of the main notations.}
\begin{tabular}{|c|}
\hline
\textbf{\( x \)} & access probability chosen by the incoming user \\
\textbf{\( x_i \)} & access probability chosen by the existing user \( i \) \\
\textbf{\( n \)} & number of existing users \\
\textbf{\( n_i \)} & number of existing users when the user \( i \) is admitted into the network \\
\textbf{\( U \)} & utility of the incoming user \\
\textbf{\( U_i \)} & utility of the existing user \( i \) \\
\textbf{\( \tau \)} & saturation throughput of the incoming user \\
\textbf{\( \tau_i \)} & saturation throughput of the existing user \( i \) \\
\textbf{\( \theta \)} & priority of the incoming user’s WTP \\
\textbf{\( \theta_i \)} & priority of the existing user \( i \)’s WTP \\
\textbf{\( \beta \)} & the maximum access probability that each user can choose \\
\textbf{\( \lambda \)} & Lagrange multiplier \\
\textbf{\( p \)} & rate of charge \\
\textbf{\( t \)} & arrival time of the incoming user \\
\textbf{\( t_i \)} & arrival time of the existing user \( i \) \\
\textbf{\( t̃ \)} & intended departure time of the incoming user \\
\textbf{\( t_\text{\textunderscore}i \)} & intended departure time of the existing user \( i \) \\
\textbf{\( \Delta t \)} & intended stay duration of the incoming user \\
\textbf{\( \Delta t_i \)} & intended stay duration of the existing user \( i \) \\
\hline
\end{tabular}
\end{table}
the user’s utility decreases below the price charged by the service provider due to congestion; and
• the user does not intend to connect any more.

In summary, the price per unit time merely depends on the user-chosen access probability. The overall payment grows proportionally with the time each user connects. If every user chooses the same access probability, the proposed pricing scheme becomes a classical usage-based pricing scheme.

5. Stackelberg Leader-Follower Game and Nash Equilibrium Solution

A Stackelberg leader-follower game is formulated to analyze the competitive interaction between the service provider and the users. We assume that the service provider and the users are rational in the sense that they are fully aware of their alternatives, have clear preferences, and take actions in order to maximize their payoffs [24]. The Stackelberg leader-follower game, $\Gamma(\text{Player, Strategy, Payoff})$, is described as follows:

• **Player**: The service provider and each incoming user are the players of this game. Specifically, the service provider is the leader and the incoming user is the follower.

• **Strategy**: For the incoming user, the strategy is the selection of access probability; and for the service provider, the strategy is the decision on whether to admit or to reject the connection request.

• **Payoff**: For the service provider, the payoff is the corresponding revenue; for the incoming user, the payoff is the net utility as shown in Eq. (7).

Applying the access-probability-based pricing, the payoff for the incoming user is given by

$$S(x) = \alpha + \theta \ln \left[1 + x \prod_{i=1}^{n} (1 - x_i)\right] - px$$

subject to $0 \leq x \leq \beta$  \hspace{1cm} (7)

Take the first derivative of $S(x)$ with respect to $x$

$$S'(x) = \frac{\theta \prod_{i=1}^{n} (1 - x_i)}{1 + x \prod_{i=1}^{n} (1 - x_i)} - p$$

As shown in Fig. 2, let $S'(x)$ equal to 0.

$$x^* = \frac{\theta}{p} - \frac{1}{\prod_{i=1}^{n} (1 - x_i)}$$  \hspace{1cm} (10)

If taking the second derivative of $S(x)$ with respect to $x$

$$S''(x) = -\frac{\theta \left[\prod_{i=1}^{n} (1 - x_i)\right]^2}{\left[1 + x \prod_{i=1}^{n} (1 - x_i)\right]^2} < 0$$  \hspace{1cm} (11)

which suggests that the function is concave down at $x^*$. Therefore, at a maximum of $S(x)$ over $0 \leq x \leq \beta$, the following condition holds.

Now looking at the service provider’s side, without the exact knowledge about the incoming user’s preference (i.e., $\theta$), the service provider has to make a decision based on the history of incoming user’s choice (i.e., $x$). Specifically, the service provider can obtain the $\theta$ through backward induction as follows.

$$x = \begin{cases} 0 & \text{if } \theta \leq \frac{p}{\prod_{i=1}^{n} (1 - x_i)}, \\ \min (\beta, x^*) & \text{if } \theta > \frac{p}{\prod_{i=1}^{n} (1 - x_i)}. \end{cases}$$  \hspace{1cm} (12)

The CAC negotiation is conducted one user after another according to their arrival time, and all the users are symmetric. Similarly, the priority of existing user $i$’s WTP can be obtained by

$$\theta_i = \begin{cases} \frac{1}{\prod_{j \neq i}^{n} (1 - x_j)} + x_i & \text{if } x_i \in (0, \beta), \\ \frac{1}{\prod_{j \neq i}^{n} (1 - x_j)} + \beta & \text{if } x_i = \beta. \end{cases}$$  \hspace{1cm} (13)

where $n_i$ is the number of existing users when user $i$ is admitted into the network, and the existing users are reordered by their arrival time.

As shown in Fig. 3, the system is dynamic in terms of the fact that users join and quit dynamically. The utility of each existing user decreases with the admission of an incoming user. For instance, when the incoming user
with access probability \( x \) is admitted, the utility of existing user \( i \) drops from \( \alpha + \theta \ln \left[ 1 + x_i \prod_{j=1, j\neq i}^n (1 - x_j) \right] \) to \( \alpha + \theta \ln \left[ 1 + x_i (1 - x) \prod_{j=1, j\neq i}^n (1 - x_j) \right] \). In case that the utility decreases below the price charged by the service provider (i.e., \( p x_i \)), the existing user \( i \) will reject the price and leave. This imposes the service provider a capacity constraint on its revenue optimization problem.

Let \( t, \bar{t}, \) and \( \Delta t = \bar{t} - t \) be the arrival time, the intended departure time, and the intended service duration of the incoming user, respectively. The revenue growth received from the incoming user is therefore denoted by

\[
R^{\text{growth}} = p x \Delta t
\]  

(15)

When each existing user adopts a myopic strategy [25], namely, the user remains connected if the price charged by the service provider is less than its utility, otherwise the user rejects the price and leaves, the revenue loss incurred by the quit of existing users is denoted by \( R^{\text{loss}} \) as follows.

\[
R^{\text{loss}} = \sum_{\alpha + \theta \ln \left[ 1 + x_i (1 - x) \prod_{j=1, j\neq i}^n (1 - x_j) \right] < p x_i} p x_i (\bar{t}_i - t)
\]  

(16)

where \( \bar{t}_i \) is the intended departure time of the existing user \( i \). Note that there is no information exchange among existing users. Namely, existing users do not know whether the other users will choose to disconnect or not due to congestion. Therefore, existing users reject the price and leave as long as their utility decreases below the price. As shown in Eq. (16), the service provider has to consider the effect that users may disconnect simultaneously due to the congestion incurred by an incoming user.

Let \( z_i \) be the network congestion indicator of the user \( i \) when it is admitted into the network.

\[
z_i = \frac{1}{\prod_{j=1}^n (1 - x_j)}
\]  

(17)

According to Eq. (14), it could be concluded that:

- if the existing user \( i \) chooses its access probability that \( x_i \in (0, \beta) \), the service provider has perfect information that \( \theta_i \) equals to \( (z_i + x_i) \rho \); 
- if the existing user \( i \) chooses its access probability that \( x_i = \beta \), the service provider can not be fully aware of \( \theta_i \); instead, the service provider confines the \( \theta_i \) to a range from \( (z_i + \beta) \rho \) to \( +\infty \). In this case, we assume that the service provider is risk-averse, and uses the minimum value, i.e., \( (z_i + \beta) \rho \) to estimate \( \theta_i \).

Let \( z_{i,k} \) be the network congestion indicator of existing user \( i \) when a late-coming user \( k \) is admitted into the network.

\[
z_{i,k} = \max(z_i, \max_k z_{i,k})
\]  

(19)

Eq. (17) can hence be transformed into Eq. (20) as follows.

\[
R^{\text{loss}} = \sum_{\alpha + \theta \ln \left[ 1 + x_i (1 - x) \prod_{j=1, j\neq i}^n (1 - x_j) \right] < p x_i} p x_i (\bar{t}_i - t)
\]  

(20)

**Lemma 1.** Assuming that the stay duration of each user follows an exponential distribution, the following strategy profile is a Nash Equilibrium.

1. The incoming user chooses the access probability

\[
x = \begin{cases} 
0, & \text{if } \alpha + \theta \ln \left[ 1 + x \prod_{i=1}^n (1 - x_i) \right] < p x \\
\max \left[ 0, \min \left( \beta, \frac{\theta}{p x_i} \right) \right], & \text{otherwise}
\end{cases}
\]

2. On the other hand, the service provider admits the connection of the incoming user if and only if

\[
x > \sum_{\alpha + \theta \ln \left[ 1 + x_i (1 - x) \prod_{j=1, j\neq i}^n (1 - x_j) \right] < p x_i} x_i
\]

**Proof.** Refer to Appendix A.
choose.

On the other hand,

- the less the number of existing users (i.e., \( n \)) is; and
- the lower access probability (i.e., \( x_i, i \in \{1, ..., n\} \)) that the existing users are bound with;

the higher probability with which the service provider admits the new connection request.

6. QoS Negotiation and Admission Control

The steps involved in QoS negotiation and admission control [26] are shown in Fig. 4(a).

**Step 1:** An incoming user arrives at the network, and detects the existence of APs via periodically broadcasted beacons. In order to reduce network management overhead, rate of charge \( p \) and the access probabilities of existing users (i.e., the congestion-indication signal) are included in the beacons as shown in Fig. 5.

**Step 2:** The user performs authentication and indicates its access probability through sending a Service Level Specification (SLS) packet. As shown in Fig. 5, the SLS packet contains: username, password, and the required access probability.

**Step 3:** The service provider decides whether or not to admit the user’s connection request.

Note that the access probability of an existing user stays unchanged during the service session unless the user explicitly changes it. As shown in Fig. 4(b), an existing user can changes its access probability by sending a SLS packet which contains the new access probability. If the request is rejected due to congestion, the user hence determines either to stay connected with the old access probability or to disconnect.

The system operates normally under the precondition that every change in access probabilities is initialized by sending SLS packet as shown in Fig. 4(b). However, users may increase their access probabilities without sending a SLS packet and may raise their saturation throughput in secret under the same price. In this paper, we assumed that a change in access probabilities can be detected by the service provider in a timely fashion. For instance, for window-based protocols such as IEEE 802.11, changing access probability can be implemented by adjusting window size, which is included in the TCP header. The change in access probabilities can therefore be detected by periodically checking the value of window size contained in the TCP header. A punishment mechanism can further be adopted in order to prevent the users from changing their access probabilities secretly. Due to space limitation, cheat prevention is out of the scope in this paper.

7. Simulation Results

As described in Sect. 3, we consider a wireless random access network where users contend for channel access according to the user-chosen access probabilities. A transmission is successful if and only if there is a single transmission attempt, namely, there is no carrier sensing, and we do not take into account the explicit back-off.

Without loss of generality, we assume that users arrive according to a Poisson process and stay for a period, which is exponentially distributed. The priority of users’ WTP is uniformly distributed within the range: \([0, 1000]\), and the access probability is uniformly distributed within the range: \([0, \beta]\). Each simulation lasts 3 hours, and is repeated for 10,000 times. Reasonably accurate results are obtained by taking average of all these repetitions. Detailed simulation settings are summarized as shown in Table 2.

In order to explore the performance of the proposed scheme, several schemes are employed for comparison.

- **Fixed** scheme: the service provider admits users straightforwardly.
- **Threshold** scheme [6]: the service provider uses a threshold value \( m \) to admit or to reject connection re-

<table>
<thead>
<tr>
<th>Table 2</th>
<th>A summary of the simulation settings.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arrival rate</td>
<td>300 per hour</td>
</tr>
<tr>
<td>Average stay duration</td>
<td>1 hour</td>
</tr>
<tr>
<td>Simulation hours</td>
<td>3 hours</td>
</tr>
<tr>
<td>( p )</td>
<td>10</td>
</tr>
<tr>
<td>Priority of WTP (( \theta ))</td>
<td>([0, 1000])</td>
</tr>
<tr>
<td>Access probability (( x ))</td>
<td>([0, \beta])</td>
</tr>
<tr>
<td>Rate of charge (( p ))</td>
<td>100, 200, 300, 400, 500, 600</td>
</tr>
</tbody>
</table>
quests. Selecting an appropriate $m$ is of vital importance. If $m$ is too small, first-coming users prevent other users with higher priority of WTP from being admitted, resulting in a revenue loss. On the other hand, if $m$ is too large, the threshold scheme degrades to the fixed scheme. In this paper, we vary $m$ and select the one with the best performance to compare.

For the other schemes, the service provider admits the connection of an incoming user as long as the potential revenue growth from the incoming user is enough to compensate for the potential revenue loss incurred by the quit of existing users.

- **Public-information scheme**: the service provider has perfect information about the priority of WTP of each user (i.e., $\theta_i$), which is not realistic and used to show the best case.
- **Private-information scheme**: the service provider is not fully aware of $\theta_i$; the service provider is assumed to be risk-averse and it uses the lower boundary value $(z_i + x_i)p$ to estimate $\theta_i$.
- **Proposed scheme**: the service provider is not fully aware of $\theta_i$ either; the service provider uses the dynamically updated lower boundary value $(z_{i,\text{max}} + x_i)p$ to estimate $\theta_i$, as described in Sect. 5.

For a fair comparison, $\beta$ is set to 0.3 for the three schemes.

As shown in Fig. 6(a), the proposed scheme and the public-information scheme outperform their counterparts in terms of increasing the total revenue. Specifically, compared to the best existing threshold scheme, the total revenue of the proposed scheme is increased by 17.9%. This is not surprising, because the service provider in the proposed scheme examines the potential revenue loss dynamically before admitting an incoming user’s connection request. With the increase of price, only the users with higher priority of WTP can be further admitted. Hence, the average revenue from each user of the proposed scheme is higher than that of the threshold scheme, which can be confirmed from the results plotted in Fig. 6(b). Furthermore, the av-

![Fig. 6](image-url)
Average revenue from each user also depends on the accuracy of estimating $\theta_i$. As shown in Fig. 6(b), the average revenue from each user of the proposed scheme is lower than that of the public-information scheme but higher than that of the private-information scheme.

The total number of users served shown in Fig. 6(c) includes: (i) the number of users that quit until the end of their sessions; and (ii) the number of users that unintentionally quit due to network congestion. Although the average revenue from each user of the proposed scheme is lower than that of the public-information scheme, as shown in Fig. 6(b), the proposed scheme served more users which accounts for the comparable performance of the two schemes in terms of total revenue as shown in Fig. 6(a).

The proposed scheme and the public-information scheme outperform their counterparts in terms of increasing the total payoff and the average payoff for each user as shown in Figs. 6(d) and (e), respectively.

In this paper, we assume that each user chooses the access probability that optimizes its payoff, while the self-interested service provider decides whether to admit or to reject the user’s connection request in order to optimize its revenue. When reaching the Nash equilibrium solution, neither a user nor the service provider can increase its payoff or revenue by deviating from its strategy unilaterally. Although saturation throughput is taken into account when users and the service provider make decisions, optimizing the saturation throughput is not the major objective from the viewpoint of either the user or the service provider. As shown in Figs. 7(a) and (b), even compared to those of the private-information scheme, the average saturation throughput per user of the proposed scheme is decreased by 24.2%; and the total saturation throughput of the proposed scheme is decreased by 11.1%, respectively. Namely, trying to optimize users’ payoff and service provider’s revenue simultaneously sacrifices the users’ saturation throughput. Generally, the more accurate information about each user’s WTP, the higher probability that the service provider can make the right decision on prioritizing the connection request of the users with higher access probability. The average access probability and the number of active users, as shown in Figs. 7(c) and (d), are regarded as the two major factors that lead to the different performance in terms of saturation throughput.

Furthermore, in order to explore the effect of parameter $\beta$ on the performance of the proposed scheme, we vary $\beta$ from 0.1 to 0.6. Other settings are held unchanged as shown in Table 2. According to Eq. (19), users with higher priority of WTP choose their access probabilities that equal to the upper bound value $\beta$. Therefore, the access probability, on average, increases with $\beta$. Some interesting phenomena are depicted and illustrated as follows.

- As shown in Fig. 8(a), the average number of active users decreases with $\beta$. This is not surprising because first-coming users with higher priority of WTP try to occupy the channel by choosing the upper boundary value $\beta$ as their access probability and hence prevent the late-coming users from being admitted into the network.
- It can be observed that the curves plotted in Figs. 8(b) and (c) level off until $\beta$ reaches 0.4. In Fig. 6 and Fig. 7, $\beta$ is set to 0.3; and the rationale behind this setting is that we want to keep both the total revenue gain as well as the saturation throughput at relatively high levels.

The rate of charge $p$ should be determined based on the distribution of WTP, load of connection requests, etc. As shown in Fig. 6 and Fig. 7, for different maximization objectives, different $p$ should be selected. For example, in order to maximize the total revenue, the optimal $p$ should be selected from the range of (300, 400), while in order to maximize the average revenue from each user, the optimal $p$ should be selected from the range of (400, 500). On the other hand, $\beta$ should be selected based on the trade-off between the total revenue gain and QoS guarantee as shown in Fig. 8. It is important to point out that the main contribution of this paper is to study the incentive-compatible interactions of the decision makers in wireless random access networks where
both $p$ and $\beta$ are preliminarily determined. Simulations can be conducted in order to get the optimal setting of $p$ and $\beta$.

8. Conclusions

In this paper, a Stackelberg leader-follower game structure is applied to obtain the equilibrium of the network resource allocation problem between the service provider and the users. The game is composed of three steps: (i) the service provider predefines a pricing scheme and provides congestion-indication signals for users; (ii) an incoming user chooses the best response strategy (i.e., access probability) to optimize the payoff; (iii) based upon the best response strategy, the service provider then decides whether to admit or to reject the user’s connection request. Simulation results show that the proposed scheme achieves higher QoS performance than the best existing schemes.

References


Fig. 8 Effect of $\beta$ on the performance of the proposed scheme.
Appendix: Proof of Lemma 1

Proof. The incoming user accepts the price $px$ if and only if

$$S(x) = \alpha + \theta \ln \left( 1 + x \prod_{i=1}^{n} (1 - x_i) \right) - px \geq 0 \quad (A.1)$$

Combining Eq. (12) and Eq. (21), the incoming user chooses its access probability as

$$x = \begin{cases} 0, & \text{if } \alpha + \theta \ln \left( 1 + x \prod_{i=1}^{n} (1 - x_i) \right) < px \\ \max \left[ 0, \min \left( \beta, \frac{\theta}{p} \frac{1}{\prod_{i=1}^{n} (1 - x_i)} \right) \right], & \text{otherwise} \end{cases} \quad (A.2)$$

On the other hand, in order to maximize the overall revenue, the service provider makes the CAC decision based on not only the revenue growth from the admission of a new incoming user, but also the potential revenue loss incurred by the quit of existing users. To be specific, a rational service provider admits the connection of an incoming user if and only if the revenue growth from the incoming user is enough to compensate for the revenue loss incurred by the quit of existing users.

$$R_{\text{growth}} > R_{\text{loss}} \quad (A.3)$$

Combining Eq. (15), and Eq. (20), the service provider admits the connection of the incoming user if and only if

$$px \Delta t > \sum_{\alpha+(\xi_{\text{max}}+\alpha)p\ln[1+x_{\xi}(1-x_{\xi})]\prod_{j=1,j\neq i}^{n}(1-x_{j})<px_{i}} px_{i}(\tilde{t}_{i} - t) \quad (A.4)$$

By applying the memorylessness property of exponential distribution, the expectation of $\Delta t$ equals to that of $\tilde{t}_{i} - t$, therefore, Eq. (25) can finally be transformed into Eq. (26) as follows.

$$x > \sum_{\alpha+(\xi_{\text{max}}+\alpha)p\ln[1+x_{\xi}(1-x_{\xi})]\prod_{j=1,j\neq i}^{n}(1-x_{j})<px_{i}} x_{i} \quad (A.5)$$

$\square$
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