A Joint Technical and Micro-economic Investigation of Pricing Data Services over Wireless LANs

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ABSTRACT

In this paper, we analyze a wireless LAN hot-spot, based on the IEEE 802.11b protocol, and more specifically we address the issue of defining proper pricing strategies, from both perspectives of evaluating technical performance and quantifying the economic revenues. We take into account a model for users' behavior that considers the trade-off between perceived QoS and paid price. This allows us to describe all users' choices in a decentralized manner, so that the transmission rate of each node is driven both by service requirements and by the customer's willingness to pay. After this setup, the multiple users' medium access mechanism is considered through simulation based on *ns-2*. Within this model, the network performance is evaluated and discussed. First, we investigate the provider's task of having a suitable price policy that gives a satisfactory income. This is connected with the goal of achieving high throughput, but is also dependent on a price setting that is accepted by the users and optimizes resource usage. Finally, we present numerical results which can provide practical insight for pricing setup in a wireless LAN hot-spot.

Categories and Subject Descriptors

C.2.1 [**Network Architecture and Design**]: network communications, wireless communication

General Terms

Management, Performance, Economics

Keywords

Rate allocation, Utility functions, Pricing

1. INTRODUCTION

A very interesting and developed application of the Wireless Local Area Networks (WLANs) based on the IEEE 802.11 protocol [1] is the creation of hot-spots, where a set of mobile terminals is connected to a central access point. This kind of system is nowadays present in business areas like conference rooms or airport and hotel lounges, where users are interested in easily and rapidly establishing a network connection.

Current implementations of IEEE 802.11 systems use the Distributed Coordination Function (DCF) using Carrier-Sense Multiple Access (CSMA). It is well known [2] that in this case the performance is heavily affected by the network operating conditions. Thus, the provider is interested in efficiently managing the bandwidth resource. Reasonably, this could mean aiming at achieving a satisfactory income from the network management operation and providing as many users as possible with a satisfactory service, which are required in order to have a sustainable economic model. For this reason, the investigations on how to properly allocate the radio resource, as well as to set up an appropriate pricing strategy, are key issues for the network operator [3].

To explore these aspects, we refer to the application of economic models to the Radio Resource Management, an open field for research on which several contributions have appeared in the recent literature. In particular, the concept of utility functions and issues taken from game-theory have been employed to represent a tunable Quality of Service (QoS), for example obtained through variations of the terminal's data rate [4, 5].

An example of application of micro-economic issues to the management of a WLAN hot-spot is given in [6]. However, note that the micro-economic control performed there refers to the definition of a virtual price that has the effect of regulating the access and is negotiated dynamically [7]. Instead, in the present contribution we are interested in considering more directly the real price established by the operator for the service tariff, which is bound to be fixed *a priori* and known in advance by the users.

In particular, our aim is to investigate the role of actual pricing in determining resource usage. Besides causing revenue generation, pricing the system usage also allows a better coordination and a more efficient utilization. In other words, price tuning can be seen as an implicit Admission Control (AC) mechanism which improves the system performance. On the other hand, too high a price prevents users from entering the service, so that the system is underutilized. Besides the total revenue, we also study the service appreciation by measuring the average number of satisfied users, which is another indicator of good management that a provider of a real system needs to take into consideration in the long run.

In order to perform these evaluations, we adopt the micro-economic model for wireless applications and services presented in [8], which describes the users' choices as driven by their appreciation of the service, and at the same time allows the evaluation of economic quantities such as the provider revenue and the average number of satisfied users.

Hence, our goal in this study is to apply such an economic model to a system characterized by CSMA/CA. This requires first of all a model extensions in order to account for the dynamically changing operating conditions of a WLAN hot-spot. Moreover, to perform this integration in a simple and direct manner, we realized it within the *ns-2* simulator [9]. Thus, after a short summary of the micro-economic model that will be used to evaluate the behavior of the users of the WLAN hot-spot, presented in Section 2, we describe the case study implemented by means of an extended *ns-2* simulator in Section 3. Moreover, in Section 4 we show the numerical results of our extensive simulation campaign and in Section 5 we conclude.

2. THE MODEL FOR USERS' BEHAVIOR

The key assumption in this work is that the users' behavior can be described as driven by two factors: the quality of the service itself, which is assumed to be estimated from a quantitative point of view via subjective testing and is therefore represented by means of a utility function $u(r)$, and the price paid for accessing the service, described by a pricing function $p(r)$. Both of them are non decreasing functions of the allocated resource r, which in the case of data applications we consider denotes the achieved data rate.

The service perception is determined by the trade-off between these two parameters, since for every user, qualitatively speaking, the larger the utility and/or the lower the price, the higher the satisfaction. According to the model presented in [8], we represent this with a *service satisfaction function* for every user i belonging to the potential users set $\mathcal{Q}$, called $A_i(u_i, p_i)$, where u_i and p_i are user i's utility and price paid. Since both utility and price ultimately depend on the rate r, we will often using a slight abuse of notation, by writing $A_i(r_i)$ for short. It is further assumed that the satisfaction function takes values between 0 and 1, so that we can regard it as a probability of the ith user being satisfied.

In the following, we will refer to $p_i = p(r_i)$ and $A_i = A(r_i)$, since it is reasonable to assume that these functions are homogeneous throughout the whole network (the extension to the case where different pricing or QoS classes are present is straightforward). Instead, we assume a different utility function for every user so as to account for the variability of services and terminals. Being a subjective factor, the utility heavily depends on factors which can not be controlled by the resource manager, such as the terminal performance or the users' evaluation of the service quality *per se*. Hence, $u_i(\cdot)$ is in general a different function for every user.

We assume that the general objective of the network manager is to have high revenue while at the same time achieving satisfaction of the users. Thus, we evaluate the revenue *on satisfied users only*. The motivation for this is as follows: from an economic point of view, dissatisfied users are expected to abandon the service in the long run and henceforth they can be considered as lost customers. For this reason, generating revenue without satisfying the users appears to be pointless.

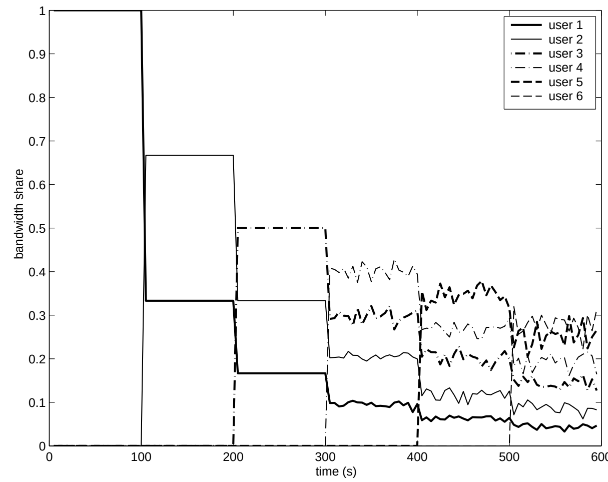

Figure 1: Proportional share of resource for a WLAN system with six users with increasing priority. This confirms and extends to a larger system the results already obtained by [12].

When dealing with WLANs based on the IEEE 802.11b, the complexity of the MAC protocol makes it difficult to deal with analytical formulations of the capacity. Even though interesting analytical models have been presented in the literature [2, 10, 11], for the sake of simplicity this paper uses results obtained with the *ns-2* simulator.

Moreover, we need a differentiation mechanism to prioritize and coordinate multiple users' requirements in the WLAN environment, which possibly imply a different rate r_i for every user. The value of r_i will then be mapped through the utility and pricing functions to finally determine the probability of accepting the service, A_i.

For investigation purposes only, we suppose that all users generate packets at the same rate, so the requested traffic of each user depends on the length of generated packets. This mechanism, together with other possibilities, has been proposed in [12]. We remark that other differentiation techniques might be used as well within the same rationale. The choice of this particular strategy is motivated by the fact that under saturation conditions the long range average traffic enjoyed by each user results to be proportional to its packet length. In particular, this mechanism allows for the ratio between the offered traffic of any two users to be the same both in the non saturated and in the saturated case.

To confirm this, Fig. 1 reproduces the results shown in [12], extended to a wider range of number of users. We consider the subsequent allocation of up to 6 users in the WLAN scenario, so that a new user is allocated every 100 seconds. The resource requirements of each user are subsequently increasing, so that the rate requested by the ith user, $i > 1$, is i times that requested by the first one. As shown in the figure, the correctness of the assumption of proportionally fair share of resources holds. However, as the number of users increases the instantaneous variations around the long range average value become more evident.

As shown in Fig. 1, the rate achieved by the users is not constant over time, and in particular varies according to the presence of other users in the network. For this reason, the rate r_i allocated to user i should be regarded as variable over time, i.e., $r_i(t)$. For the purpose of a practical evaluation, and also in order to account for the fact that the users' re-evaluation of their service perception is not instantaneous, we sample the time axis so that each user re-considers its acceptance of the service every ΔT seconds.

If user i enters in service at time t_i and its call duration request is T_i seconds, $\lfloor \frac{T_i}{\Delta T} \rfloor$ service evaluations might occur at most, beyond the first one at the time the user is allocated in the system. The call is successfully completed if and only if all these tests are passed. In particular, $r_i^{(0)}$ is the rate requested by user i before entering the system. This rate is assumed equal to the allocation which maximizes its satisfaction probability, i.e.,

$$r_i^{(0)} = \arg\max A(r_i)\,. \tag{1}$$

For $0 < j \leq \lfloor \frac{T_i}{\Delta T} \rfloor$, $r_i^{(j)}$ is instead defined as the average rate perceived up to the jth evaluation, i.e.,

$$r_i^{(j)} = \frac{1}{j\Delta T}\int_{t_i}^{t_i+j\Delta T} r_i(t)\mathrm{d}t\,,$$

where t_i is the start time of user i's service.

Note that the values of $r_i^{(j)}$, with $j > 0$, are meaningful only if the user hangs to the service continuously, since if the user refuses the service its allocated rate drops to zero. In order to evaluate this aspect, we define, by exploiting the concept of *conditional probability*, the conditional acceptance of r_i' given that r_i was an acceptable assignment as:

$$A(r_i'|r_i) = \begin{cases} \frac{A(r_i')}{A(r_i)} & \text{if } A(r_i') \leq A(r_i) \\ 1 & \text{if } A(r_i') > A(r_i)\,. \end{cases} \tag{2}$$

The call of user i is successfully completed with probability

$$P_i(\text{complete\_service}) = A_i(r_i^{(0)}) \prod_{j=1}^{\lfloor T_i/\Delta T \rfloor} A_i(r_i^{(j)}|r_i^{(j-1)})\,.$$

Otherwise, we distinguish between the case in which the service is evaluated as unacceptable already at the first evaluation, which happens with probability $1 - A_i(r_i^{(0)})$, and the case of service refusal in a subsequent evaluation, when the user is already in the system, whose probability is

$$A_i(r_i^{(0)})\left(1 - \prod_{j=1}^{\lfloor T_i/\Delta T \rfloor} A_i(r_i^{(j)}|r_i^{(j-1)})\right).$$

In the former case the user is said to be *blocked*, in the latter to be *dropped*. In particular, we define

$$P_i(\text{drop\_instant\_}k) =$$
$$= A_i(r_i^{(0)})\left(\prod_{j=1}^{k-1} A_i(r_i^{(j)}|r_i^{(j-1)})\right)\left(1 - A_i(r_i^{(k)}|r_i^{(k-1)})\right)$$

which is the probability that the user is dropped at the kth evaluation.

The distinction between blocked and dropped correctly reflects that users can refuse the service due to their own a priori decision of not entering the system, for example because of the price being too high, or can experience unacceptable service degradation due to a congestion arisen in a second time. As is well known, the impact on the QoS of these events is considerably different. The reason for explicitly classifying also blocked users is that considering pricing implies that the system is admission controlled, as discussed in the introduction and also as will be numerically shown in the following.

In this way, our previously discussed revenue evaluation can be rigorously formalized as follows. We want to evaluate the revenue R as the sum of paid prices, but subdividing it between the contributions determined by satisfied and dissatisfied users, respectively.

A satisfied user i will pay in the end a price $p\big(r_i^{(F)}\big)$ determined by the rate $r_i^{(F)}$ perceived on its entire service connection, which is:

$$r_i^{(F)} = \frac{1}{T_i}\int_{t_i}^{t_i+T_i} r_i(t)\mathrm{d}t\,.$$

The revenue generated by satisfied users, $R^{(s)}$, is therefore determined as

$$R^{(s)} = \sum_{i\in\mathcal{Q}} p\big(r_i^{(F)}\big) P_i(\text{complete\_service}) \tag{3}$$

For what concerns dissatisfied users, blocked ones do not generate revenue at all. The value $R^{(d)}$, which is the potential revenue generated by dropped users, is instead equal to

$$R^{(d)} = \sum_{i\in\mathcal{Q}} \sum_{k=1}^{\lfloor T_i/\Delta T \rfloor} P_i(\text{drop\_instant\_}k)\, p\big(r_i^{(k)}\big)\,. \tag{4}$$

For our evaluation it does not matter whether in the end dropped users pay or not. Either virtual or real, a high revenue generated by dropped users is an index of inefficiency, since it means that part of the resources have been wasted to be allocated to dissatisfied users. For this reason, a suitable provider's goal could be to increase $R^{(s)}$ and decrease $R^{(d)}$ at the same time, or at least to cut a trade-off in this trend.

3. CASE STUDY

To validate the aforementioned model, we have run experiments with the *ns-2* simulator. We consider a Hot-Spot scenario with a single IEEE 802.11b Access Point (AP) in the center of a 32 m $\times$32 m square area. Propagation effects and mobility have been implemented with already available *ns-2* modules, determining a radio scenario affected by slow fading with pedestrian mobility of the terminals.

The main element of the simulator is the so-called wNode, a typical node of *ns-2*, which we provided with some additional features to account for the micro-economic behavior of the WLAN users. We implement the model of Section 2 in order to drive the choices of the users in terms of selecting the most suitable transmission rate, as the trade-off between paid price and gained utility, so as to eventually evaluate the supplied QoS.

Also, in order to support the users' prioritization due to their different rate requirements, we focus on a CBR service over UDP with constant packet generation rate, so the contention process within nodes is always fair but the time of transmission, and hence the bytes transmitted, are proportional to the priority represented by the *requested rate* $r_i^{(0)}$. In this way, we aim at representing real-time interaction with the traffic. Note however that this choice can be

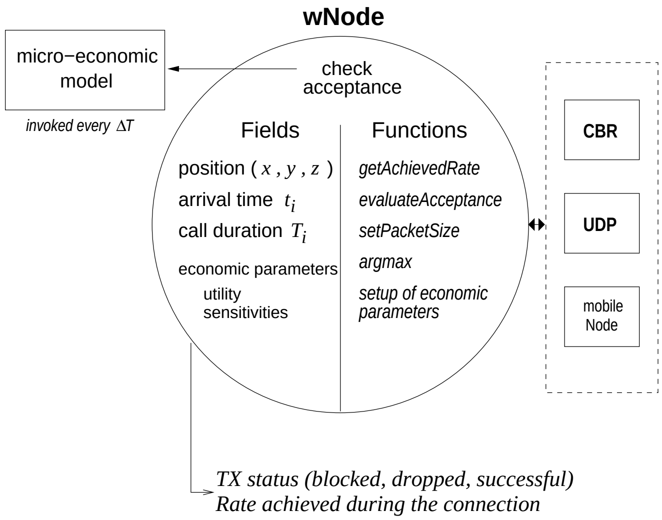

Figure 2: The central unit of the simulator: the wNode

easily and directly replaced within the simulator by more complicated choices. The scheme of the wNode, as well as some implemented functions, are reported in Fig. 2.

The users behave dynamically, coming and going from the Hot-Spot and setting up connections of different types in terms of duration and transfer rate. The arrivals are Poisson with arrival rate λ. For what concerns the service duration, we also assume Poisson distribution with parameter μ; however, the users might leave the system if they consider the service dissatisfactory (this is why the exit process is no longer Poisson when dissatisfied users begin to appear). The ratio λ/μ is still useful to understand how many users on average would be under service if the dissatisfied users did not abandon the system.

The micro-economic model previously discussed is used to evaluate the users satisfaction and is implemented in a distributed manner at each node. Essentially, there are three kinds of events that matter in the system: a new node establishing a connection, a node ending its connection due to successful service completion (these two are regulated through the Poisson parameters λ and μ) and finally the evaluations of the users about their service, which might determine a premature termination due to dissatisfaction in the service received.

When a user i arrives to the system, the simulator evaluates at first $r_i^{(0)}$ as described by Eq. (1). With probability $A(r_i^{(0)})$, the user accepts to establish a connection at rate $r_i^{(0)}$, and in this case the duration T_i of the connection is also determined. Then, the user is added to the system directly through the already implemented *ns-2* functionalities. This means that the rate provisioning of $r_i^{(0)}$ is not guaranteed, due to the possible presence of other users. It is possible that the transmission rates no longer match the initial requirements because of congestion, this means that for wNode i the perceived rate r_i is lower than $r_i^{(0)}$. In general, we can regard $r_i^{(0)}$ as the *requested* rate, and every value $r_i^{(j)}$ with $j > 0$ as the *achieved* rate after $j\Delta T$ seconds, keeping in mind that the achieved rate is not necessarily equal to the requested one (in case of congestion it is indeed lower), but due to the fair sharing property of IEEE 802.11 discussed in Section 2 the two values are roughly proportional to each other. For this reason, in the simulator, every $\Delta T = 20$ seconds the achieved rate is re-evaluated, based on the conditional probability given by Eq. (2).

At the end of the simulation run, users can be subdivided in terms of how their transmission ended: as described in Section 2 there are blocked users that do not accept to establish the connection at all; also, other users may accept their initial transmission rate, but when it decreases due to other arrivals they perceive it is too low and so they exit from the system, i.e., they are dropped users; finally, there are users that finish their transmission in a satisfactory manner.

For what concerns the pricing, we considered two cases, in order to test how different pricing strategies impact on the system performance:

- *LINEAR PRICING STRATEGY*: $p(r) = \alpha \cdot r$
- *FLAT PRICING STRATEGY*: $p(r) = q_f$,

where both α and q_f are proper positive parameters, chosen by the provider a priori (hence known to all users) and considered as tunable values to change the price and therefore represented as the independent variables in the graphs.

Note that we have chosen these expressions in order to provide a qualitative comparison of two different possibilities. Also other pricing strategies can be tested with the very same approach presented here, especially hybrid policies between flat and linear pricing which might indeed might be more realistic.

4. RESULTS

As a general comment, price variations influence the system in a complex way, in terms of both users' throughput and provider's revenue. This relation is revealed by an *implicit admission control*, created by pricing the resource and therefore allowing the users to self-manage the system access. A better understanding of this relation between pricing and system welfare is developed considering two different pricing strategies, i.e., linear and flat pricing.

We show the results of our evaluation in Figures 3–6. Figures 3 and 4 refer to the linear case. In particular the former shows how users are subdivided in the system, considering the three categories already explained; on the other hand, the latter shows how the revenue is split between satisfied and dropped users (blocked users are not considered as they do not generate revenue). Moreover, in both cases four different values of the tunable parameter λ/μ are considered, where an increasing value leads to a more congested system. In the same way the results are shown for the flat pricing strategy in Figures 5 and 6.

The linear case shows a discrimination in terms of users' utility. In fact, increasing the unit price, i.e., the parameter α, implies a higher penalty for the users with high requested rate and/or low utility. As a result, the revenue obtained by the provider with a linearly-dependent pricing is not very high, since users tend to regulate their request to cheaper resource allocations, but this also means that a high percentage of satisfied users is obtained, as the users have more freedom in their choice. This discrimination somehow prevents high-demanding users from entering the system or in most cases from completing the call. It can be said that this way of pricing the network service is a way for the provider to perform implicit admission control; note that the self-regulated access of the users is performed on the basis not

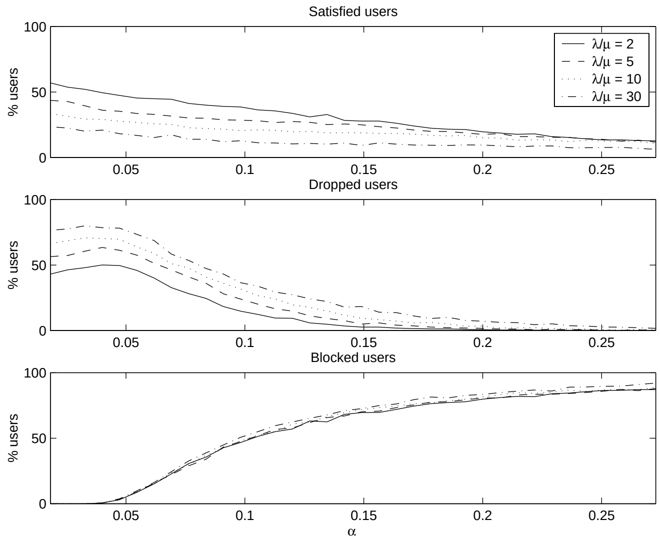

Figure 3: Users' dynamics with linear pricing

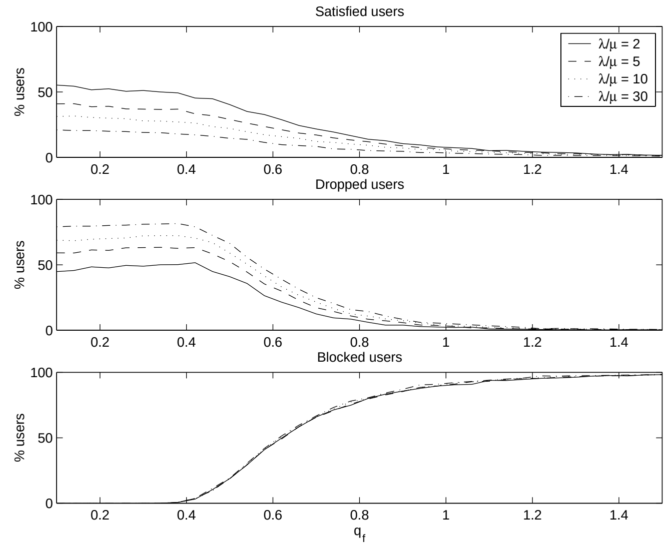

Figure 5: Users' dynamics with flat pricing

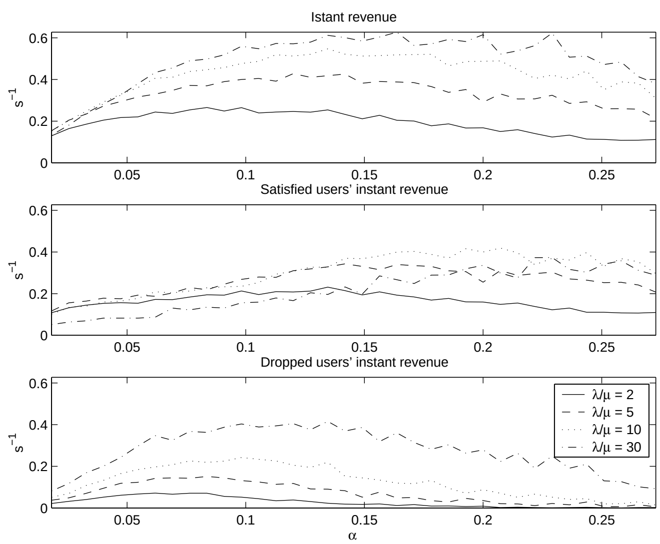

Figure 4: Revenue's dynamics with linear pricing

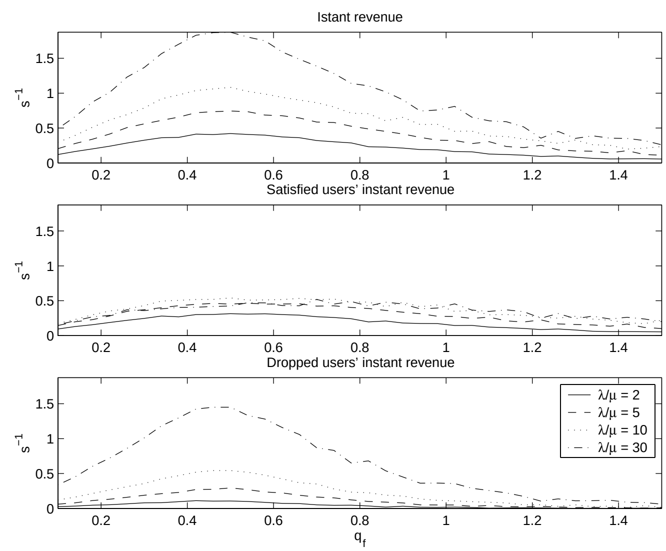

Figure 6: Revenue's dynamics with flat pricing

only of their perceived utility but also of their reaction to the price, which is in this case proportional to the rate request. These facts are in general the reason for a lower revenue, but also for higher stability of the performance (observe in fact the smoother shape of the curves).

On the other hand, the flat case also applies implicit admission control, but in the same way to all the users, whereas the linear case was adaptive to their requests. This implies that every user simply asks for the transmission rate which gives the highest utility, since the maxima of utility and acceptance probability occur for the same rate value. Due to the increasing behavior of the utilities, this is obtained when the rate is as high as possible (which would be 11 Mbps, but indeed in the simulator this value is capped at 5 Mbps, which is a more realistic estimate of what can be achieved in practice).

Therefore, flat pricing leads both to higher rate requests, and also to increased revenue. Compared to the linear pricing case in fact, from the individual perspective of the users the fixed price to pay regardless of the rate seems to be relatively cheaper, if the requested rate is high, although it is higher in absolute terms. However, the price that the users (and hence also the provider) pay for these improvements is an increasing congestion and therefore an overall decrease in the users' satisfaction.

These properties of the flat pricing strategy make it not suitable in general. However, it might be a good choice in a class-based scenario for business customers, i.e., for a limited number of users with top requirements and therefore willing to pay more. Instead, to manage the majority of the customers without strong quality requirements, a usage-based linear pricing is more efficient.

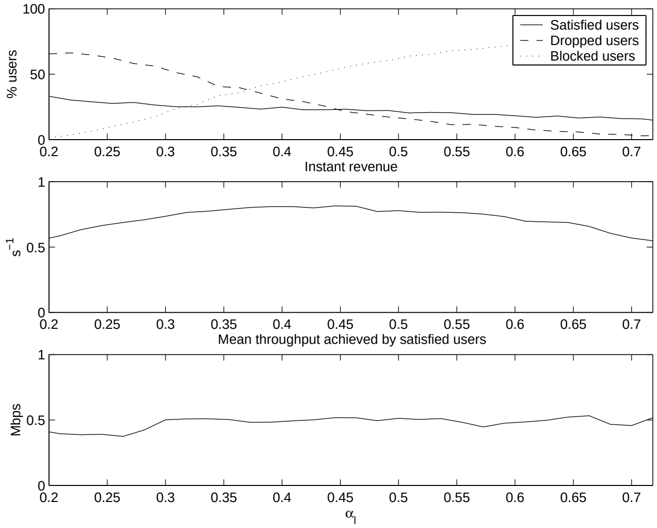

Figure 7: Dynamics in high congestion situation

We considered also the number of users that can be served at the access point in a satisfactory manner, working at maximum revenue. Fig. 7 shows the users' distribution, revenue and throughput (evaluated on satisfied users only) achieved with linear pricing under conditions of extreme congestion (i.e. $\lambda/\mu = 30$). Note that that revenue is maximized for $\alpha \approx 0.4$, which is more or less the point in which blocked users become a considerable fraction, and, as a consequence, at the same time dropped users are decreased. This shows the effectiveness of a proper linear pricing setup in managing the admission to the system and regulating congestion so as to obtain revenue efficiency.

In a realistic scenario, the number of users that can simultaneously share the channel with satisfactory performance is not very high, at most we found approximately 7 users transmitting at 0.5 Mbps each, for a resulting very limited throughput compared to the available bandwidth. For a provider, this means that congestion and pricing-based competitive management of the users decrease the AP capacity.

Moreover, the results show that increasing the number of users in the system leads to a saturation of the revenue of satisfied users. A smarter distribution of the AP that subdivides the customers according to these considerations could lead to a higher welfare for both the users and the provider.

5. CONCLUSIONS

We studied RRM and pricing policies for a WLAN hotspot, considering both technical and economic perspectives. The goal of achieving a satisfactory revenue is decomposed into two objectives, namely good network efficiency and high appreciation from the users. To represent this aspect, we applied a micro-economic framework to describe users' choices in a decentralized way.

The results obtained through the *ns-2* simulator, modified in order to describe the users' behavior as driven by micro-economic aspects, show that the overall behavior of the system is strongly affected by the micro-economic management. This is true for the throughput, the generated revenue (and especially the relationship between the revenue generated by satisfied vs. dissatisfied users), and the number of allocated users.

Thus, an appropriate choice of the pricing policy is key for the provider to obtain good system performance. In particular, the pricing strategy should be able to regulate the users' access in order to prevent users from achieving dissatisfactory service due to congestion.

Moreover, there are tight inter-dependencies between pricing and efficiency of the IEEE 802.11 protocol that can be studied with our model and whose correct evaluation is useful not only for the provider's network planning, but also for possible further improvements of the protocol efficiency.

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