Radio Resource Management with Utility and Pricing for Wireless LAN Hot-spots

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Abstract. We investigate Wireless LAN hot-spots based on the IEEE 802.11b protocol, considering technical and economic issues of the Radio Resource Allocation. Firstly, we discuss how to model the trade-off between perceived QoS and paid price in the users' request, so as to represent the users as choosing the most satisfactory allocation, determined by service requirements and willingness to pay. After the setup of the users' requests, the multiple medium access mechanism is considered and the network performance is evaluated and discussed. Thus, we investigate the provider's task of having a suitable price policy which gives a satisfactory income and efficiently exploit network capacity. This is also dependent on a price setting that is accepted by the users and optimises resource usage. Finally, we study how the multiple access scheme specified in the IEEE 802.11b protocol combines users' requests to a final allocation, and identify possibilities of improvement for the inherent inefficiencies arising from overload.

Keywords: Radio Resource Management, Wireless LANs, Utility, Pricing

1. Introduction

Wireless Local Area Networks (WLANs) are nowadays present in everyday life. In particular, the IEEE 802.11b protocol [1] has emerged as a good and flexible platform to implement single-hop WLAN hot-spots. This success is due to the possibility of easily establishing a network connection; this explains why IEEE 802.11b WLAN hot-spots are so commonly found in campuses, airports, conference rooms, hotel lounges and other business areas. In particular, IEEE 802.11b systems are currently implemented by means of Carrier-Sense Multiple Access with Collision Avoidance (CSMA/CA) in the Distributed Coordination Function (DCF). It has been shown [2,3] that the performance of such networks is heavily dependent on the scenario and on the network load.

The goal of this paper is to study the efficiency of the Radio Resource Management (RRM) from the perspective of the network operator. About this point, the provider's goal can be identified in achieving an adequately high value for several metrics of interest, like the number of satisfied users or the total amount of data exchanged. Moreover, the commercial success of establishing a WLAN hot-spot heavily depends on the operator's capability of pursuing a high revenue [4]. Indeed, these different goals are also strictly connected, and in all of them the price at which the service is provided plays an important role; this is caused by the market relationship between the operator and the customers, which likely do not exchange data and refuse the service if it is too expensive.

To this end, we study in the present paper the integration of the CSMA capacity of the IEEE 802.11b systems [3] with a scenario in which the users require different levels of Quality of Service (QoS) and react to pricing. In this case, the WLAN hot-spot management is affected by many parameters, in particular it is very sensitive to the users' behaviour, which is then driven by the trade-off between paid price and perceived QoS. Micro-economic criteria can be applied to the management of the radio access, in the sense of both considering distributed strategic choices made by the users and applying tariffs for the service.

In the recent literature [5–7], several proposals have appeared, studying radio resource allocation with micro-economic instruments, in particular for WLANs. As a result, one can identify possibilities of quantifying money exchange but also improving the users' appreciation of the management, as the evaluation of the QoS might be taken into account within the objectives of the management as well. In this context, the pricing strategy plays a key role. In fact, besides generating income, pricing the resource usage may improve the efficiency by implicitly coordinating the competing users. In other words, price tuning can be seen as an implicit Admission Control (AC) mechanism, which improves the system performance [8] and it is also applicable and beneficial to WLANs [9].

We will proceed as follows: first of all, we assume that the users' requests depend on their appreciation of the service, derived from the "QoS vs. price" trade-off. Secondly, we try to evaluate, in view of this distributed allocation mechanism, the revenue that the provider can earn.

In more detail, we assume that users might request any value of transmission rate within a certain continuous interval, which determines the perceived QoS, described by means of a utility function, and also the payment of a tariff proportional to network usage, i.e. users are charged proportionally to the rate [10]. Note also that the resource usage implies a multiplexing among all users, with a constraint determined by the available bandwidth and the CSMA/CA mechanism, so that the resource allocation must be compatible with inherent protocol limitations. We use these two parameters, utility and price, within a model of users' behaviour [11]. In this way we can investigate, by considering different values of the price, the impact of the pricing policy on the income. We show that a network allocation can be efficiently set only by dimensioning the price according to the users' reaction to it. Moreover, we vary the number of users in the network to study the impact of network load demand. The main conclusion of this investigation is that both technical and economic performance change significantly according to the number of users, so that this parameter should be carefully accounted for in dimensioning the network. As a more general conclusion, the comparison between classic measures of technical efficiency of the management, such as throughput, and economic issues, such as revenue, show that a joint analysis of these two sometimes contrasting aspects is necessary in order to reduce inefficiencies.

This work is organised as follows: in Section 2 we model the behaviour of the WLAN users by including micro-economic considerations concerning the QoS. In Section 3 we integrate this model with the CSMA/CA capacity of the IEEE 802.11b hot-spot. Then, in Section 4 we implement the integrated model in a simple idealised scenario to obtain general results about the allocation, and in Section 5 we extend the framework in order to take into account characteristic aspects of the IEEE 802.11b protocol. Finally, Section 6 concludes the paper.

2. A Model of WLAN Users' Behaviour

In this paper we focus on a particular kind of WLAN, specifically the IEEE 802.11b infrastructure-based implementation, realised with the DCF. In other words, mobile terminals are connected to an Access Point (AP), i.e. a centralised unit for the whole hot-spot.

In such a scenario, it is very interesting to characterise the users' behaviour. WLAN terminals have extremely variable features and are often utilised to access a plethora of services. Moreover, the issue of QoS provisioning has in general gained increasing attention in wireless networks and is particularly challenging for small networks with protocols, which, like IEEE 802.11, are intrinsically best effort (at least in the original concept), i.e. there is no guarantee about the QoS possibly achieved. Other aspects, like mobility and power consumption, further complicate the RRM. Even though these topics are not directly within the scope of the present paper, it is possible to extend the framework presented here to include them.

Thus, under the perspective of QoS supply, the RRM is very difficult to investigate, since users' appreciation of the service is often hard to represent with analytical tools. Therefore, a way commonly followed in the recent technical literature is to employ utility functions [5, 12–14], which are an instrument derived from micro-economics. In particular, in [4, 7] these concepts have been applied to WLAN scenarios. For the purpose of the present paper, a utility function simply describes the relation between the amount of allocated resource and the perceived QoS, e.g. estimated from a quantitative point-of-view via subjective testing.

However, we are interested in studying micro-economic aspects not only from the theoretical point-of-view, but also for what concerns the impact of network management on the market; thus, we include also tariff collection in the analysis. This has an immediate effect on the operator's strategy, which can include among its objectives also to earn as much as possible from network operation, in addition to other economic metrics such as having a large number of customers or fully allocating the available resource. Nevertheless, there is also a side-effect on the users' choices: if a pricing is considered, they may not necessarily prefer high quality allocations, which might be very expensive, but instead the trade-off between QoS and price must be considered.

To take into account these facts, we represent the behaviour of the users in terms of service appreciation by means of the model we developed in [11]. According to this model, an acceptance rate $A_i(u_i, p_i)$ is defined for each user i. The user index i ranges between 1 and N, which is the total number of users. The parameters u_i and p_i, called utility and price of the ith user respectively, mathematically represent the QoS perceived and the tariff paid, and both depend on the resource assignment for user i, that we will describe with a unique parameter called r_i. We assume that both utility and price are non decreasing functions of r_i.

Thus, we write $u_i = u_i(r_i)$ and $p_i = p_i(r_i)$ and $A_i = A_i(u_i(r_i), p_i(r_i))$. However, if we assume that all users belonging to the system adopt similar criteria to evaluate service appreciation, we use the same function $A_i(\cdot) = A(\cdot)$ for every user, without the index i. For fairness reasons, it is sensible that the tariff plan is well-known a priori by the users, that is also the pricing $p_i(\cdot) = p(\cdot)$ is the same for all the users. Note that these conditions are not restrictive and can be easily removed by a class-based approach in which price and service appreciation are differentiated among the users. This is realistic if different services are allowed, but in the present paper we limit the analysis to a homogenous market where the kind of service is the same for all users. Hence, the subscript i will be omitted for the functions $A(\cdot)$ and $p(\cdot)$, while it will be kept when speaking of the actual values A_i (or p_i) achieved (or paid) by user i, which may be different for different users.

The utility function is instead assumed to be different for every user 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, we consider a different $u_i(\cdot)$ for every user.

To sum up, we need to characterise the function $A_i = A(u_i, p_i)$ as a function of two variables u_i and p_i, having contrasting but similar effects on the evaluation of the service acceptance, since A_i decreases as u_i decreases and/or p_i increases. The usual approach to regulate such trends in economics [15] is to define parameters called *sensitivities*, which in our case describe how A_i changes according to variations of u_i or p_i. We introduced two parameters, called ε and μ, to represent the sensitivities to pricing and QoS, respectively. These values can be tuned to account for different kinds of markets, where users are more sensitive to price or to utility variations.

As A is bound to stay within a $0-1$ range, the following expression can then be suitable for our purpose [11]:

$$A(u,p) = 1 - e^{-ku^{\mu}/p^{\varepsilon}}. \tag{1}$$

The multiplicative constant term k is simply a normalisation constant which depends on the sets of values of u and p. In our simplified case where $A(\cdot)$ is the same for all users, k, μ and ε are network constants. The exponential shape introduced in Equation (1) implies that for small values, i.e. $A \ll$, the function is proportional to u^{μ} for fixed p, where it is inversely proportional to p^{ε} for fixed u.

We discuss now how utility and price are dimensioned, to fully specify the above model. The utilities considered in the rest of the paper are upper-limited functions. This is done according to technological constraints, because it is realistic to assume that the users' ranking of the QoS can not be improved beyond a certain limit, which depends on human perception or inherent limitations of the terminal. Also, technological constraints impose an upper limit to resource assignment, since it is not possible to indefinitely assign resource to users.

This implies that there is a range of feasible allocations, i.e. $r_i \in [0, \mathcal{T}]$ for each user. If there is no other more stringent constraint, the upper limit $\mathcal{T}$ is the total available resource. This interval is translated by the non decreasing function $u_i(\cdot)$ into another interval, which is not restrictive to take as $[0, 1]$. Thus, in the following we consider that for every user i, $0 \leq u_i(0) \leq u_i(\mathcal{T}) \leq 1$. For what concerns p_i, we can follow a similar reasoning by considering a linear pricing (henceforth strictly increasing).

3. Integration with the CSMA/CA Capacity

The above framework can be applied to the IEEE 802.11b hot-spot, by identifying the resource assignment r_i with the transmission rate *requested* by user i. We assume that r_i can be regarded as a continuously tunable variable. In this case, $u_i(r_i)$ and $p(r_i)$ are the instantaneous utility and the instantaneous price paid corresponding to the allocation of the rate r_i. However, this is an approximation, made for the sake of simplicity, since these quantities indeed depend on the final value allocated to the user, which is called in the following ρ_i. Due to the distributed structure of WLANs, there is no guarantee that ρ_i will be actually equal to the requested rate r_i. In general, ρ_i depends also on the rates $r_1, \ldots r_N$ requested by other users, so that $\rho_i \leq r_i$ for every i and the equality is guaranteed to hold only when the total requested resource is much less than what is available.

Our analysis has henceforth two objectives: first of all, to preliminarily investigate how the users react to their first service evaluation, i.e. when only r_i is known. Then, we approach the problem of evaluating the relationship between ρ_i and r_i by means of simulation. To consider r_i instead of ρ_i only for the users' evaluation greatly simplifies the analysis and avoids more complex relationships due to the CSMA/CA capacity.

Both r_i and ρ_i should not be confused with the signalling rate, called s_i, which relates to the physical transmission of data over the shared channel. When the IEEE 802.11b standard is adopted, the signalling rate belongs to the set $\mathcal{S} = \{1, 2, 5.5, 11\}$ Mbps, according to the channel conditions between the terminal and the AP. Roughly speaking, we might think, as in the commercial card specifications [16], that the choice of a value of s_i in $\mathcal{S}$ mainly depends on the distance to the AP. The signalling rate s_i is the maximum transmission rate allowed to the ith user, whereas r_i depends on the actual fraction of time user i is able to access the channel, and is upperbounded by s_i. In other words, r_i can be chosen in $[0, \mathcal{T}]$ where $\mathcal{T} = s_i$ and $s_i \in \mathcal{S}$.

We use the previously discussed micro-economic framework to identify the most preferrable transmission rate r_i as:

$$r_i = \arg \max_{r \in [0, \mathcal{T}]} A(u_i(r), p(r)) \,. \tag{2}$$

Equation (2) means that each user tries to get the rate maximising its own service acceptance. Note that the eventual assignment for user i will be ρ_i and not r_i, hence resulting in a lower service acceptance ratio. In fact, if r_i is chosen as the most preferrable rate, any other assignment will be less appreciated. Thus, this evaluation is conservative because it accounts for a larger number of users than the ones actually accepting the final assignment. However, it is still useful to approach the relationship between $A(\cdot)$ and r_i in the simplest way, though approximate.

The meaning of A_i, whose value belongs to $[0, 1]$, is to indicate how satisfactory the service is considered in terms of both quality and price. In this view, we can give a probabilistic meaning to A_i by assuming that on average, if the acceptance rate is A, a fraction of users exactly equal to A will accept the service conditions. We can use the following method to evaluate the performance once users' requests are known. Importantly, even though r_i is selected by user i as the most satisfactory value of the requested rate, the probability that this user will eventually accept the service is not one, but it is given by A_i. Thus, the total average number of users trying to access the service is

$$S = \sum_{i=1}^{N} A(u_i(r_i), p(r_i)) \tag{3}$$

and the total average requested rate can be evaluated as

$$T = \sum_{i=1}^{N} r_i A(u_i(r_i), p(r_i)). \tag{4}$$

The latter evaluation is however done *a priori*, because the final outcome of the allocation will be lower in general, as we must consider the ρ_i's instead of the r_i's. This also means that for what concerns the income for the operator, we could evaluate it by considering

$$R = \sum_{i=1}^{N} p(r_i) A(u_i(r_i), p(r_i)), \tag{5}$$

which from the above discussion is an upper bound achieved only when $\rho_i = r_i$ for all i. However, another alternative will be to consider

$$R' = \sum_{i=1}^{N} p(\rho_i), \tag{6}$$

i.e. an *a posteriori* evaluation of the tariffs paid by the users for what they really get ($\rho_i = 0$ if user i decides not to accept the service). Even this evaluation, which is the subject of the preliminary investigation performed in [17], is not completely realistic, because when several users are present in the network, not only ρ_i is likely to be much lower than r_i, but also the acceptance rate will be clearly overestimated. Henceforth, in this paper we adopt a mechanism that, by means of simulation, iterates the decision process made by the users. This means that after the first dimensioning of the allocation, made by considering r_i as the allocated rate, the users re-evaluate their decision according to ρ_i, which is really what they get. However, if there are other users leaving the network, because of ρ_i being considered unacceptable, the resources are re-allocated so that another set of values of the ρ_i's is determined. This is repeated until a convergence point is found, which results in a revenue evaluation called $\widetilde{R}$. For complexity reasons, this re-allocation is performed in a sequential manner, as will be explained in the results Section. A similar reasoning can lead to the estimation of the network welfare U where the single user utilities are considered instead of the paid tariffs, i.e.:

$$U = \sum_{i=1}^{N} u(r_i) A(u_i(r_i), p(r_i)). \tag{7}$$

Also for this metric, different estimations U' and $\widetilde{U}$ can be performed analogously to what done for R' and $\widetilde{R}$, respectively.

Other design choices made in the sequel are as follows. Note that the economic model identified above does not depend on these assumptions, the only requirement being that they satisfy the intuitive properties mentioned above (i.e. that both $u_i(\cdot)$ and $p(\cdot)$ are non decreasing functions of the rate). Besides, the assumptions made in this paper, which are quite common in the literature [18, 19], have been chosen only for the sake of simplicity and are not intended as more realistic than others.

The utilities are described by the following formula:

$$u_i(r) = \frac{(r/\chi_i)^{\zeta_i}}{1 + (r/\chi_i)^{\zeta_i}}. \tag{8}$$

where $\chi_i \in [0, \mathcal{T}]$ and $\zeta_i > 1$ are tunable parameters. To obtain a different utility function for every user, χ_i and ζ_i are randomly generated with a distribution that depends on the scenario. However, the values are selected so that $u_i(\mathcal{T})$ is very close to 1, which happens if $\chi_i \ll \mathcal{T}$.

Instead, the price is a linear function of the allocated rate. To dimension and normalise it, we assume that the unit price is the one which an assigned fraction A_0 of users consider to be fair if it is paid for the highest utility (which is also 1). For example, $A_0 = 10\%$ means that one user over ten considers acceptable to pay a price equal to 1 for receiving a service with utility equal to 1. This means that the value of the constant k can be determined from Equation (1) as:

$$k = -\log(1 - A_0)\,. \tag{9}$$

Thus, $k = -\log 0.9$ is obtained in the example above.

Table I. List of Parameters of Simulation Scenario

Parameter	value
utility parameter ζ_i	uniform in $[2, 10]$
utility parameter χ_i	uniform in $[0.0125, 0.125]$
acceptance prob. parameter μ	2
acceptance prob. parameter ϵ	4
acceptance prob. parameter k	$-\log 0.9$

4. Analysis of the ideal CSMA/CA scenario

In this Section we present some revenue evaluations obtained within the above framework. We simulate a scenario consisting of an AP and N terminals placed in an area of 32×32 square meters. We intend to represent in this way an IEEE 802.11b hot-spot, even though we refer to this as *idealised* IEEE 802.11b scenario, since we neglect for the moment some aspects, such as the evaluation of collisions and the role of exponential backoff. Simply, users share the medium in an equitable manner according to their requested rate. This assumption will be removed in Section 5, where a more detailed analysis will be carried out. For the sake of simplicity we also assume here that users arrive and are consequently allocated one at time. This allows us to adopt a simpler sequential approach.

In such an environment, according to realistic technical specifications of commercial WLAN cards [16], the AP has full coverage of the whole network and a signalling rate equal to $s_i = 11$ Mbps can be reached by all the terminals. It is reasonable to focus on this small area, otherwise multi-hop capabilities may have to be advocated, even though they are not natively implemented in current realisations. However, we derived other results for larger scenarios, where different signalling rates are used, and the behaviour is qualitatively similar. So we infer that the results we show in the following can be translated with appropriate adjustements to more general scenarios as well.

In this first approach, the users choose a transmission rate between 0 and $\mathcal{T} = 11$ Mbps, so that higher rates will correspond to a more aggressive channel access strategy. Other micro-economic parameters are summarised in Table I.

In the following we will consider a set of potential users which may or may not enter the service, according to the micro-economic criteria defined in Section 3. The data rate allocation will be further defined in Section 5 as connected to the arrival rate of the packets, since the users will be specified to have Poisson packet arrival processes.

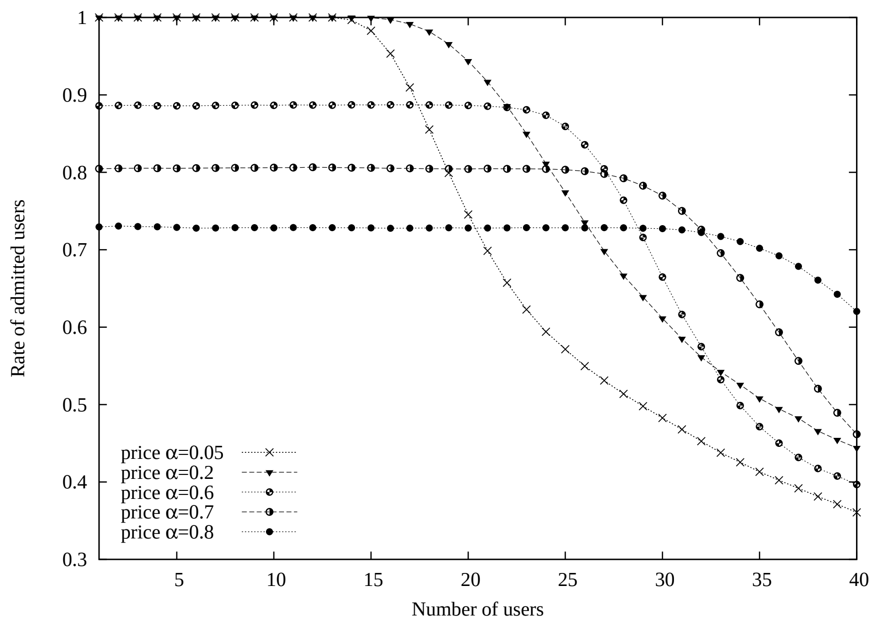

Figure 1. Number of admitted users as a function of the load

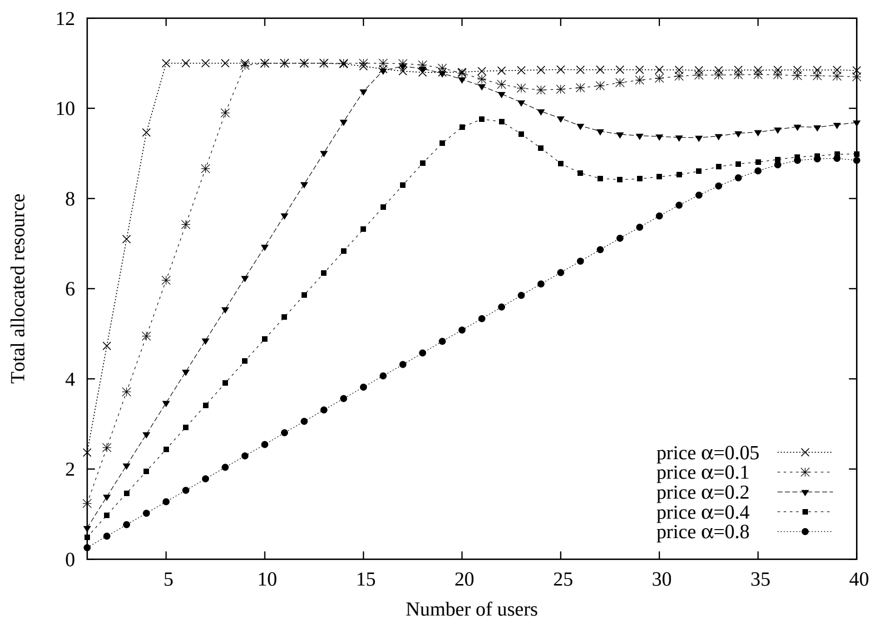

Figure 2. Total allocated resource as a function of the load

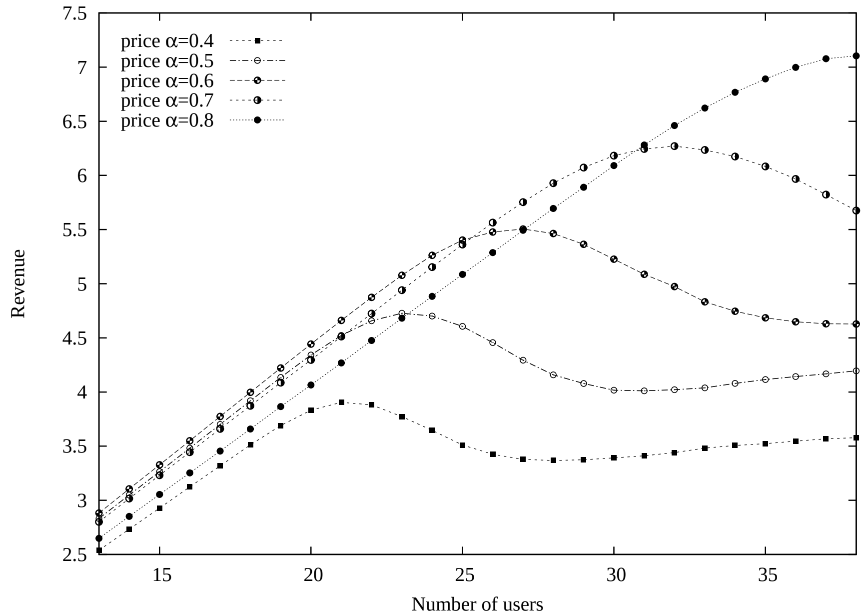

Figure 3. Total revenue as a function of the load

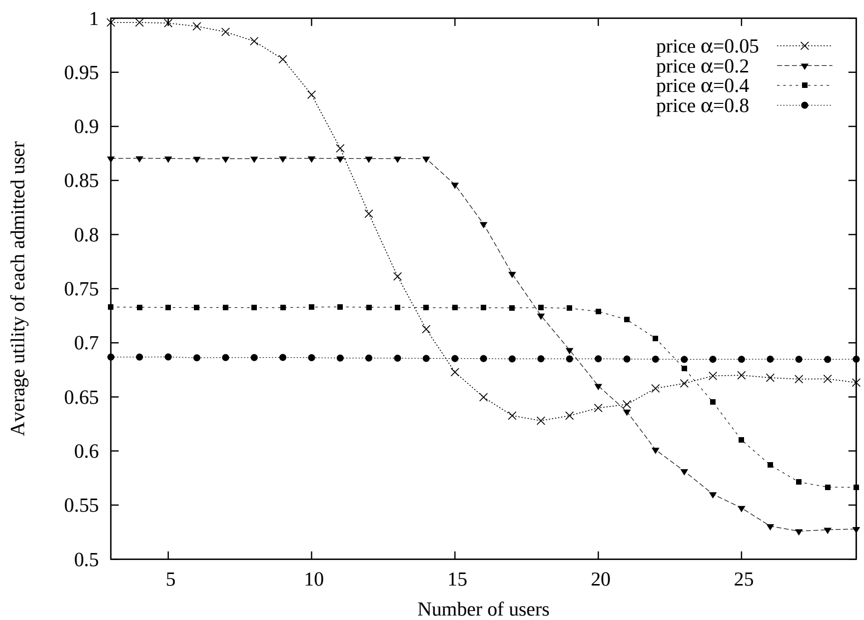

Figure 4. Average utility per admitted user as a function of the load

Each terminal tries to gain access to the channel and achieve a rate assignment. However, we neglect losses due to buffer overload, collisions and also the overhead of RTS/CTS exchange. Our idealisation of the CSMA/CA is, for this first investigation, that users can always be sequentially allocated until the channel capacity is saturated. Then, we assume to have perfect elasticity of the bandwidth, so that if the new user's request causes the available bandwidth to be exceeded, the allocation vector is rescaled in order to satisfy the bandwidth constraint. Formally, to allocate user i we check whether $\sum_{j=1}^{i} \rho_j \leq \mathcal{T}$. If this condition is violated, the actual allocation for every user j, $j \leq i$, is redefined as:

$$\rho_j \mathcal{T} (\sum_{k=1}^{i} \rho_k)^{-1}. \tag{10}$$

In this way the allocations are iteratively decreased, so it might happen that the achieved data rate (especially for users with low index) is significantly lower than the requested allocation r_i. For this reason, after each re-allocation, we re-evaluate the acceptance probability with a conditional approach [20]. This means that to determine the acceptance probability of users which are re-allocated, we proceed by considering the concept of conditional probability [21]: if two assignments r_i and r'_i are characterized by Acceptance probabilities equal to A_i and A'_i, respectively, the *conditional Acceptance probability* of accepting r'_i given that r_i was acceptable will be

$$\begin{cases} A'_i/A_i & \text{if } A'_i \leq A_i \\ 1 & \text{if } A'_i > A_i \end{cases} \tag{11}$$

We might expect that in this way the capacity eventually saturates, provided that a sufficiently large number of users is demanding service. However, the number of allocated users will not indefinitely increase, because unsatisfied users will leave the service. In this way, our investigation here is different from the one performed in [22]. The values plotted in the following are all related to the final result of iterative reallocation of resources. This means that e.g. the estimate of the revenue and the network welfare are the ones called $\widetilde{R}$ and $\widetilde{U}$, respectively.

First of all, we consider the user admission rate in Figure 1. Recall that we treat users as admitted or blocked simply according to their own decision of whether or not to enter the system, even though of course this decision is related to the QoS provided. If the possible assignment has either low utility or too a high price, the users will refuse the service. Hence, in Figure 1 it is highlighted that at low load values the admission rate depends only on the price, and the larger the price, the lower the fraction of users accepting the service. However, this statement does not hold any longer as the set of users requiring admission increases. Since a higher price has also the effect of decreasing users' requests, in certain cases to increase the tariff might be beneficial in order to save capacity and admit more users. This is the case for example in the choice of $\alpha = 0.2$ instead of $\alpha = 0.05$, which is a less efficient setup under this point of view [1]. For higher values of the price, the admission rate at low loads decreases, but still there are regions in which a higher price becomes more efficient.

In Figure 2 the total amount of allocated resource, which can be seen as a throughput estimate, is plotted. Clearly, the throughput increases at first linearly, then saturates. In case of low price, this means that a constant value is kept, but for higher α's there are peaks due to the disturbing effect of new users which degrade the rate for already allocated ones. Thus, the total allocated resource is not monotonically increasing, as discussed before.

Since we are dealing with linear pricing, the amount of resouce allocated is connected with the revenue, as shown in Figure 3. We can also conclude that the price setup which gives the highest revenue depends on the load. For example, when the number of potential users is above 30, the provider can achieve high revenue by setting the highest values of the price, but this would be inefficient when the load is below 25, because the achieved revenue (and also the admission rate) would be lower.

Finally, in Figure 4 we present the average utility achieved by each admitted user. One can see that the perceived QoS is subject to oscillations, according to the number of users in the network. In this sense, high values of the price offer more efficient coordination, because they select the most willing-to-pay users, and the achieved QoS is almost constant.

5. Extended analysis with CSMA/CA capacity

To develop the analysis presented above in more depth, we must analyse the correlation between the requested rate r_i and the obtained rate ρ_i. In particular, the main point is that the results previously shown are realistic for what concerns the trends exhibited, but not for the numerical values, since the throughput, and henceforth the revenue and other related metrics, are highly overestimated. This is due to the

[1] The value $\alpha = 0.05$ can be regarded in all the results of this paper as a case where the price is so low that the service is accepted at any condition, unless the proposed rate is 0, or very close. In other words, the curves with $\alpha = 0.05$ correspond to considering the pricing effect as negligible.

fact that the losses of the CSMA/CA mechanism, which prevent the network from reaching exactly the maximum theoretical limit of $\mathcal{T}$ were neglected.

To consider a more realistic application of the framework, we develop a detailed simulation of a CSMA/CA-like MAC, where the resource is allocated to the users according to the mechanism explained below, that makes it possible to evaluate collisions and consequent rescheduling of packet transmissions due to exponential backoff.

In more detail, we proceed as follows. We consider a timeline of 10 seconds of transmission, where we schedule packets belonging to different users. The arrival process is Poisson, so that the exponential inter-arrival times account for different traffic generation rates of the users (which are according to the model discussed in Section 2). Users are still allocated sequentially, in order to save computational complexity; the approximation introduced in this way is negligible. Thus, the first allocated user can be allocated wherever on the timeline. From the second on, every time a schedule of packets overlap, the CSMA/CA mechanism is modelled as follows. If the overlap is above a threshold, the packet with the earlier transmission time is kept, whereas the other one is rescheduled with an exponential backoff. In this way we mean to simulate the fact that the second user has sensed the transmission of the first one and has rescheduled the transmission.

Instead, if the transmission starting points of the packets are scheduled closer than this threshold, i.e. the overlap occurs during the vulnerability time, a collision arises. This means that both packets are considered as lost and both users enter the backoff process. In the simulations, the vulnerability time has been set to 88 μs.

After the evaluation time of 10 seconds, the *a posteriori* analysis of the achieved rate is started, which means that the dynamic reaction of the users to possible rate degradations is evaluated. Unsatisfied users are then removed until the allocation vector converges. Even though the simulation is very heavy from the computational point of view, it is also very accurate, so that the obtained values are more realistic from the technical perspective.

The results shown in the following concern the same four metrics discussed in Section 4, but evaluated within the more realistic CSMA/CA simulator. Figure 5 shows the admission rate as a function of the number of potential users. Since now the service degradation is better modelled and evaluated, the results are more adherent to the intuitive property that the higher the price, the lower the admission rate. This also implies that the CSMA/CA is better able to coordinate the users than a simple equitable share of bandwidth.

In Figure 6 the total allocated resource is plotted. As we are dealing with a more realistic CSMA/CA model, the values are closer to the throughput achieved by a IEEE 802.11b WLAN. The behaviour is similar (a linear increase then a saturation) to the simplified case plotted in Figure 2 but it is interesting to observe that the saturation values are very sensitive to the price. This is due to the fact that when the price is high, users tend to request small data rates and the overhead becomes relatively larger. Again, the revenue, plotted in Figure 7, follows the throughput since the pricing is linear.

Finally, Figure 8 shows the average utility achieved by admitted users. Since now collision might arise at each load level, there are utility decreases even when a number of potential users larger than 1 are present, and a saturation to an asymptotic value. Apart from the presence of a more strictly monotonic behaviour, the performance in terms of achieved QoS is more or less similar for this system and the simplified access mechanism discussed in Section 4. For example, note that the curve for large price exhibits a more stable performance and also a higher asymptotic value, which is a similarity with Figure 4.

As a general remark, we observe that the results are qualitatively similar to the ones shown in Section 4. Thus, we infer that for a simple qualitative analysis a preliminar investigation, where the inherent MAC characteristics are neglected, is sufficient. Naturally for a more detailed analysis and also for a realistic numerical evaluation, the specific MAC protocol must be taken into account in some way. However, a trade-off between these two approaches is currently under investigation, to seek if it is possible to join numerical accuracy and fast evaluation of the results.

6. Conclusions

We presented several issues to characterize the technical and micro-economic dimensioning of an IEEE 802.11b WLAN hot-spot. In particular, we focused on a model driven by users' preferences to capture the role of the distributed management provided by IEEE 802.11b DCF.

We investigate several related goals, which might be included in the provider's objective, like achieving a satisfactory income or a high number of admitted users. In every case we emphasize the dependence on factors like high network efficiency but also wide user appreciation, which can be accounted for thanks to the introduction of economic parameters into the analysis.

The results we derived by means of simulations with different levels of accuracy show that the studied system is very sensitive to economic

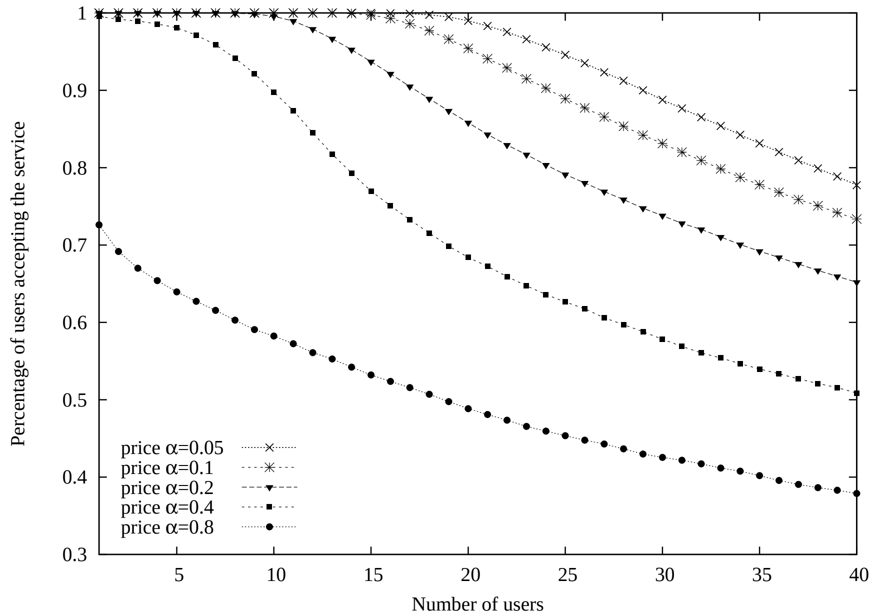

Figure 5. Number of admitted users as a function of the load

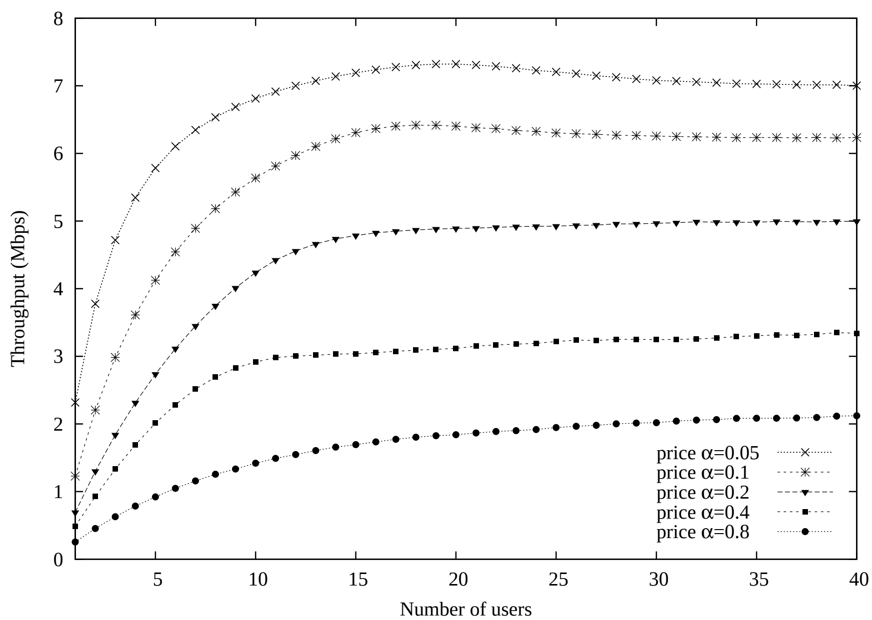

Figure 6. Network throughput as a function of the load

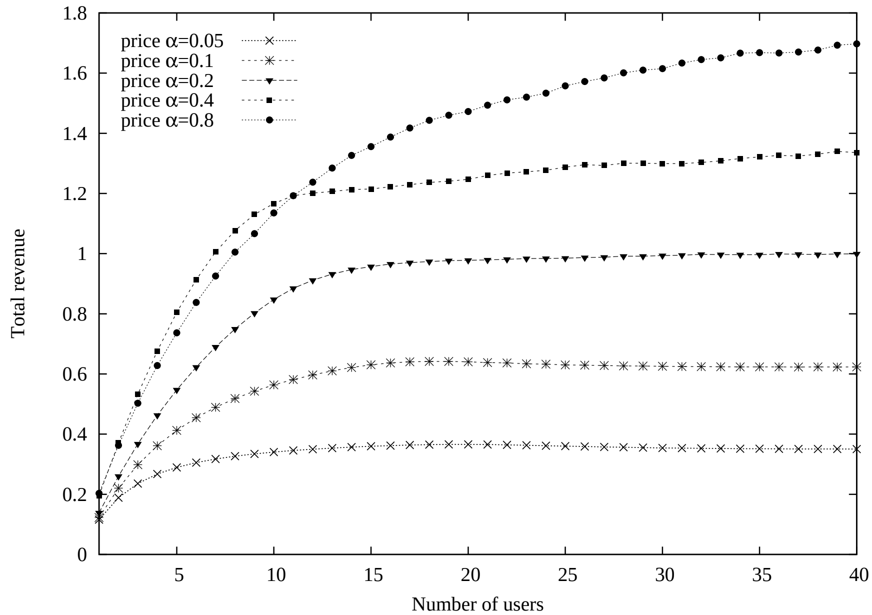

Figure 7. Total revenue as a function of the load

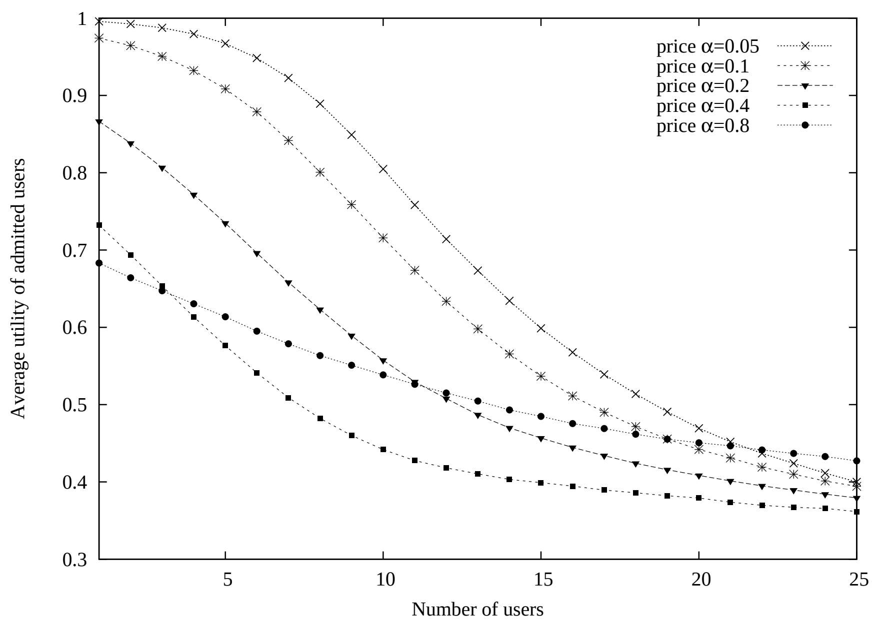

Figure 8. Average utility per user as a function of the load

aspects such as price and user satisfaction. Thus, considering the pricing setup is crucial for a proper evaluation of the system performance.

Another conclusion is that the pricing can be used to influence the number of users requesting admission, thereby realizing an implicit admission control mechanism, but the task of regulating this effect is far from easy, and must be carefully investigated via preliminary analysis.

Moreover, even though the qualitative conclusions are valid for every kind of WLAN, the realistic adherence to a given MAC protocol is possible only with appropriate models. On the other hand, our model allows to study the cross-relationships between pricing and protocol efficiency. Thus, apart from network planning, our study is also useful to investigate possible ways to improve the protocol efficiency.

Finally, we remark that the simulation analysis of the CSMA/CA protocol can be computationally heavy when iterative decisions (like re-evaluation of the service performed by the users in case of QoS degradation) are to be considered. Currently, a trade-off is sought between the two contrasting aspects of good numerical results and limited evaluation time, in order to open up the possibility of embedded implementations for micro-economic driven RRM.

Acknowledgements

This work has been supported by Ericsson Research.

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