On the Radio Resource Pricing for Wireless LAN Hot-spots

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***Abstract*— In this paper, we study the performance of a wireless LAN hot-spot by including the pricing of the Radio Resource. We consider a model for users' behaviour that accounts for the trade-off between perceived QoS and paid price, so that the transmission rate of each node is driven by both service and tariff impact. Within this model, the network performance is evaluated and discussed. We investigate the provider's task of having a suitable price policy which gives a satisfactory revenue. Moreover, we also analyse the service appreciation rate and the sensitivity to the number of possible system customers. Finally, we extended these considerations to gain general insights on the impact of the pricing on wireless LANs.**

I. INTRODUCTION

The creation of Wireless Local Area Network (WLAN) hot-spots based on the IEEE 802.11 protocol [1] is nowadays enjoying great popularity. IEEE 802.11 WLAN hot-spots are present in airports, conference rooms, hotel lounges and other business areas. They are an easy and flexible way to establish a network connection. In particular, IEEE 802.11 systems are currently implemented by means of Carrier-Sense Multiple Access (CSMA) in the Distributed Coordination Function (DCF). However, the performance of such a network is heavily dependent on the scenario and network load [2]–[4].

In this paper, we study which is a desirable management from the point-of-view of the network operator. It is sensible to assume that the provider's goal is to have a satisfactory revenue. This includes also, as subtasks, the efficient use of the network resource and adequate satisfaction of the users, otherwise the service would generate too low an income and its business model would not be sustainable. We analyze such a scenario by considering the provider capability of managing the resource assigned to the users. In particular, our first goal in this study is to integrate the CSMA capacity of an IEEE 802.11 system with related issues of the hot-spot access. In particular, we aim at considering the service price as a tunable variable which affects the final performance.

To do so, we apply a model for the users' behavior that considers the trade-off between perceived QoS and paid price, which allows us to consider all users' choices in a decentralized manner. Several proposals to keep into account economic aspects of Radio Resource Management (RRM) have appeared in the recent literature [5]–[8]. It is important to know that micro-economic concepts can be employed first of all to quantify money exchange but also to improve the efficiency of the management, as the users' welfare might be taken into account within the objectives of the management as well. Moreover the role of pricing has to be stressed: in fact, besides generating income, pricing the resource usage improves the efficiency by allowing implicit coordination and regulation of the users which compete for the resource. In other words, price tuning can be seen as an implicit Admission Control (AC) mechanism which improves the system performance.

We use these economic considerations to model at the same time the users' choice driven by their appreciation of the service and the revenue that the provider can earn. In particular, we proceed as follows: first of all, we assume to have tunable quality differentiation mechanisms, which allow to priorize users differently, as outlined in [9]. Secondly, we integrate a micro-economic model of users' behavior [10] with the users' multiplexing constraint given by the CSMA/CA mechanism. In particular, we apply a linear pricing strategy, which seems to be reasonable for such a network, where the requested amount of resource heavily affects the performance. Hence, users are charged proportionally to the rate they get [11].

Under this framework, we investigate first of all how the pricing policy affects the income, by showing that the efficiency of this part depends on the users' appreciation rate of the price setting. Moreover, besides the price setting, we also study the users' demand and the effect of load variations. These two aspects have non-trivial effects on the performance, and in particular on the total revenue; hence, a provider of a real system needs to take them into consideration. Finally, we will identify a trade-off between classic measures of technical efficiency of the management, like the throughput, and economic issues. On this matter we will show that a joint analysis of these two sometimes contrasting aspects might improve the understanding of the system.

This work is organised as follows: in Section II we model the behaviour of the WLAN users by including micro-economic considerations concerning the QoS. In Section III we present and discuss the simulation results and finally Section IV concludes the paper.

II. THE MODEL FOR USERS' BEHAVIOUR

We represent the behaviour of the users in terms of service appreciation by means of the MEDUSA model [10]. According to this model, an acceptance probability $A_i(u_i, p_i)$ can be defined for each user i ($1 \leq i \leq N$, with N being the total number of users) as a function of two parameters u_i and p_i, the former being the utility coming from the service itself (which is assumed to be estimated from a quantitative point-of-view via subjective testing) and the latter being the price paid. Both of them are non decreasing functions of the resource given to the users, and they will be dimensioned as explained in the sequel. Formally, if r_i is the resource assignment for the ith user, we could write $u_i = u_i(r_i)$ and $p_i = p_i(r_i)$. For the sake of simplicity, we assume that the service appreciation is a uniform among the market, which means to use the same function for $A_i(\cdot) = A(\cdot)$, i.e., independently of i. Also it is reasonable that the pricing is, for fairness reasons, the same for all the users, since the tariff plan is well-known a priori by the users. These conditions can be easily removed by considering a class-based approach in which price and service appreciation are differentiated among the users since different degrees of service (and even different services) are allowed, but there is no point in introducing them if the users represent a homogenous market and use the same service. Hence, the subscript i will be omitted for $A(\cdot)$ and $p(\cdot)$. Nevertheless, the actual value of these functions will still be indicated as A_i and p_i, as it depends in the end on the actual resource assignment which may be different for every user. On the other hand, $u_i(\cdot)$ is different for every user even in the simplest case, since the utility coming from the service mainly depends on other factors, like the session level of the user or the terminal properties, which are assumed here to be highly variable. In this case, a different function of every user will still be considered. Hence, the MEDUSA model corresponds in our case to the characterisation of the function $A_i = A(u_i, p_i)$ (the same function for all users), where $u_i = u_i(r_i)$ (a different function for each user) and $p_i = p(r_i)$ (the same function for all users).

In this paper we identify the resource r_i with the transmission rate requested by the ith user. In this case, $u_i(r_i)$ and $p(r_i)$ are the instantaneous utility and the instantaneous price paid due to r_i. This assumption needs to be briefly remarked and discussed. We are considering rate requests made a priori by the users, so that, due to distributed structure of WLANs, there is no guarantee that the requested rate r_i will be equal to the actually obtained transmission rate ρ_i. In this paper, for the sake of simplicity, we carry out the analysis by assuming that the users evaluate the service at the beginning, i.e., when only r_i is known. Anyway, the value of ρ_i is correlated to r_i, at least intuitively. Even though no trivial relationship can be imposed to correlate r_i and ρ_i (since ρ_i depends also on the rates $r_1, \ldots r_j, \ldots$ requested by every other user), we assume, only for what concerns the users' process of evaluating the service, to consider r_i instead of ρ_i. In this way we avoid to take into account complex relationship due to the CSMA capacity. Moreover, we use the MEDUSA model to identify the most preferrable transmission rate r_i as:

$$r_i = \arg\max_{r \in \mathcal{S}_i} A(u_i(r), p(r)) \;, \tag{1}$$

where $\mathcal{S}_i$ indicates the range in which r_i spans, that will be discussed below. Equation (1) means that each user tries to get a rate which is the most preferrable for him. This condition, besides being realistic, corresponds to conservatively dimensioning the network, since it is likely that if an Acceptance-probability evaluated on the ρ_i's was considered, some users would have refused the service due to the lower satisfaction. In fact it is likely, though not mandatory, that $A(\rho_i) \leq A(r_i)$, since $\rho_i < r_i$, but the above Equation is still reasonable since keeps $A(\cdot)$ as a function of r_i.

Note that we also assume that r_i can be regarded as a continuously tunable variable. However, r_i should not be confused with the signalling rate s_i. The IEEE 802.11b standard [1] specifies different signalling rates in the set $\mathcal{R} = \{1, 2, 5.5, 11\}$ Mbps, according to the distance between the terminals. For the model application, the signalling rate corresponds to the maximum transmission rate allowed to the ith user, so that $r_i \leq s_i$. Hence, the transmission rate for user i is $r_i \in \mathcal{S}_i = [0, s_i]$, where $s_i \in \mathcal{R}$. There are several possibilities to tune the value of r_i so that the users can be prioritised differently, as outlined in [9]. In this work, we adopt a simple mechanism which considers a variation of the packet length according to the rate requested by the user. This means that users with the same signalling rate might have different transmission rates if their packet lengths are adjusted accordingly. The possibility of requesting a rate equal to 0 is introduced to mathematically represent users who do not consider the service acceptable, and therefore do not request any resource assignment at all.

The value of A_i, which is bound to be in $[0, 1]$, indicates how satisfactory the service is considered in terms of both quality and price. The goal of this paper is to evaluate the final performance by giving these requests from the users to the resource allocator. After the choice of r_i as most satisfactory requested rate, it is still not sure that the user will accept the service, in fact the acceptance has a probability equal to $A(u_i(r_i), p(r_i))$. The average requested rate will then be $r_i A(u_i(r_i), p(r_i))$. For what concerns the income for the operator, we could evaluate it in two ways: the first one is to determine $\sum_{i=1}^{N} p(r_i) A(u_i(r_i), p(r_i))$, which can be seen as an upper bound, since from the above discussion, $p(\rho_i) \leq p(r_i)$ as $p(\cdot)$ is an increasing function. The second one is to consider $\sum_{i=1}^{N} p(\rho_i)$, i.e., evaluated a posteriori, so that the actual revenue is the sum of tariffs paid for what the users really get. Note that these value are the same if only one user is present in the network. Otherwise, it is possible that congestion arises or simply the DCF mechanism reduces the effective rate, so that the transmitted data and the corresponding revenue are smaller. In particular, when the network is severely congested, $\rho_i \ll r_i$, so the previously discussed upperbound is loose.

In [10] we considered the following parametric expression for the acceptance probability:

$$A(u, p) = 1 - \exp(-k u^{\mu} / p^{\epsilon}), \tag{2}$$

where the exponents μ and ϵ allow to change the shape of A by tuning the users' sensitivity to utility and price, respectively. The multiplicative constant term k depends on how utility and price are normalised. Note that, we can consider a more general expression of A_i dependent also on the user index i, by introducing different k's, μ's and ϵ's for each user.

Equation (2) can be justified as follows: if A is small, it states that the value of A for fixed p is proportional to u^{μ} and vice versa for fixed u it is inversely proportional to p^{ϵ}. Hence, μ and ϵ can be estimated by evaluating the number of users accepting the service conditions for different prices and utilities.

To have reasonable values for the A_i's, the utility and the price must be appropriately normalised. In economics, it is commonly assumed that the derivative of the utility, though positive, approaches 0 for large r. In other words,

$$\lim_{r \to \infty} \frac{\mathrm{d} u_i(r)}{\mathrm{d} r} = 0 \quad \forall i \,. \tag{3}$$

From a more practical point-of-view, we simplify this assumption by considering upper-limited utilities, as this fits well with technological constraints. In fact, the users' perception of the QoS for real communication services can not be indefinitely improved. We impose the following further conditions: firstly, $u_i = 0 \iff r_i = 0$ for all i, which means that all assignment larger than 0 have a positive utility. In other words, the probability of accepting a very poor QoS might be small, but is never exactly 0. Moreover, it is possible to identify an upper-limit for the utility, called ψ, so that u_i belongs to $[0, \psi]$ for every i. For the normalisation, we can translate this interval to $[0, 1]$. In the sequel we model the utilities with the following formula:

$$u_i(r) = \begin{cases} \kappa \, (r / \kappa \mathcal{M})^{\zeta} & \text{if } r \leq \kappa \mathcal{M} \\ 1 + \frac{(\kappa - 1)(r - \mathcal{M})^{\zeta}}{(\kappa \mathcal{M} - \mathcal{M})^{\zeta}} & \text{if } r > \kappa \mathcal{M} \end{cases} \tag{4}$$

where $\mathcal{M} = \max \mathcal{R} = 11$ Mbps, and $\kappa \in [0, 1]$ and $\zeta > 1$ are tunable parameters, whose ranges depend on the scenario.

The price is instead not upper-limited, so several normalisations could be introduced to map the actual price $P(\cdot)$ into the normalised price $p(\cdot)$. In the following we employ this notation: let φ be the fee that is considered fair for maximum utility (i.e., for $u = 1$), by an average fraction A_0 of users, say 10%. Hence, $p(r_i)$ will be the fee $P(r_i)$ divided by φ. Thus, the following alternative expression holds, with P instead of its normalised version p:

$$A_i = \widetilde{A}(u, P) = 1 - \exp(-k u^{\mu} (P/\varphi)^{-\epsilon}) \,, \tag{5}$$

so that the boundary condition $A_0 = \widetilde{A}(1, \varphi)$ determines k as:

$$k = -\log(1 - A_0) \,. \tag{6}$$

Note that the MEDUSA model can be used even with different utility or price specification. The only requirement is that they satisfy the intuitive properties said above (i.e., being a non decreasing function for both $u_i(\cdot)$ and $p(\cdot)$ and also the law of diminishing marginal utilities for $u_i(\cdot)$ only). The assumptions made in this paper of having sigmoid-shaped utilities functions and a linear price are quite common in the literature [12], [13]; however, they are made here only for the sake of simplicity and not because they are considered optimal or more realistic than others.

Parameter	value
size of the environment	$32 \times 32\text{m}^2$
gain at 1 m	-20dB
Hata path loss exponent (β)	3.4
Fading	not considered
carrier frequency	2.4GHz
utility parameter ζ	uniform in $[2, 5]$
utility parameter κ	uniform in $[0, 1]$
acceptance prob. parameter μ	2
acceptance prob. parameter ϵ	4

Tab. 1. List of Parameters of Simulation Scenario

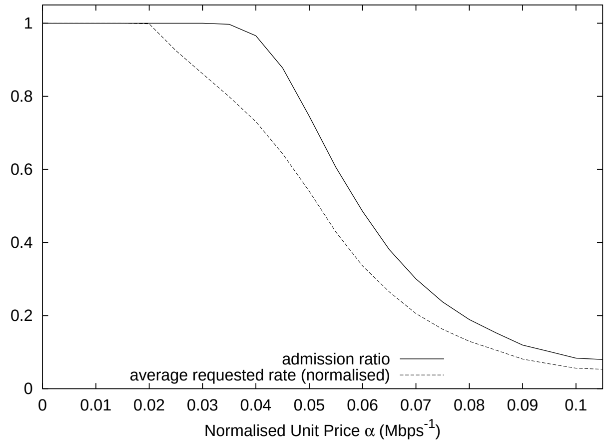

Fig. 1. Fraction of users accepting the service and normalised average requested rate per user as functions of α

III. Results

In this Section we present some revenue evaluations obtained within the above framework. We simulate a scenario consisting of a hot-spot with an IEEE 802.11b access point (AP) and N terminals placed in an area of 32×32 square meters. The signalling rate depends on the distance between the terminal and the AP, and this technological constraint has been regulated according to the specifications of an actual commercial card [14]. In our case, with the above dimensioning of the area, the AP has full coverage of the whole network (which is realistic, since in real IEEE 802.11b devices multi-hop capabilities are not natively implemented). Moreover, a signalling rate (i.e., a maximum transmission rate) equal to $s_i = \mathcal{M} = 11$ Mbps is allowed for all the terminals. Other results, not shown here for lack of space, have indeed been derived for larger scenarios (so that different signalling rates coexist), showing entirely similar trends.

We used a simulator developed at the University of Ferrara which gives a detailed description of Ad Hoc Networks. However, for the analysis presented here we did not consider mobility nor routing schemes, thus the scenario is quite simplified being the nodes fixed and the AP always in line-of-sight. The propagation parameters are summarized in Table 1, and represent a quite standard scenario. In such a scenario, the general performance of the WLAN, hence also the provider's revenue, is heavily affected by the offered load.

To gain understanding on how the price plays a key role, consider Figure 1, where we evaluate by means of simulations the fraction of users accepting the service and their requests. This is done according to the MEDUSA framework, i.e., the fraction of users requiring service can be analytically seen as $\left(\sum_{i=1}^{N} A(u_i, p_i)\right)/N$, and the average required rate is equivalently $\left(\sum_{i=1}^{N} r_i A(u_i, p_i)\right)/N$. The latter value is normalised to the highest case $\mathcal{M} = 11$ Mbps, to have comparable scales. The decreasing demand of service for increasing price can be seen not only from the decreasing number of users, but also from the lower average requested rate. It is clearly highlighted how the price is able to tune (but in certain cases, also to dramatically decrease) the number of users accepting to pay the tariff requested by the provider. Also the requested rate decreases, according to the condition of maximising $A(u_i, p)$ (if the price is higher, a lower assignment is preferrable). This can be useful in determining efficient network operating conditions, which have been shown [2] to be highly dependent on the number of users in the network.

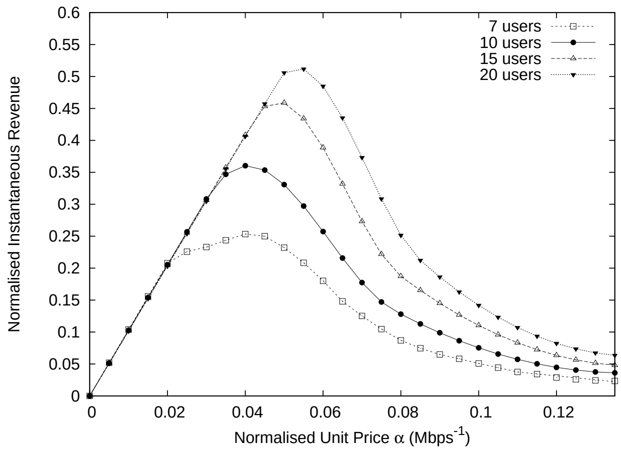

Fig. 2. Instantaneous normalised revenue for pricing $p(r_i) = \alpha r_i$ as a function of α

For this reason, in all the following results we consider a set of potential users which may enter the service or not, according to the MEDUSA model. In general, we consider Constant Bit Rate (CBR) users which generate data at a given rate: in particular, we are interested in having high input data rate, so that the network is likely to be congested. Each terminal tries to gain access to the channel and transmit its own traffic. However, we neglect losses due to buffer overload. We are only interested in determining the revenue, evaluated *a posteriori* as $\sum_{i=1}^{N} p(\rho_i) = \sum_{i=1}^{N} \alpha\rho_i$. We plot the values obtained by averaging a large number of simulations, in which the users' requests determine the terminal rates. The consequent overall throughput and revenue have been evaluated by considering 5 minutes of transmission.

Consider now the case in which a traffic of 1600 kbps is generated by each user. Note that this implies approximately that the network is congested, since the capacity of $\mathcal{M} = 11$ Mbps is already fully allocated when the number of users is larger than 7. In this case, if two or more users are in the network, we can expect that the bottleneck of the RTS/CTS causes a performance decrease. In Figure 2 the revenue per second earned by the provider is plotted as a function of the unit price α. Four different load conditions, with 7, 10, 15 and 20 potential users respectively, have been considered. It can be easily seen that this metric is heavily affected by the price setting, so that the choice of the pricing strategy (in this case, the choice of α) is not trivial. Note that when the price is low (below 0.025) all users try to enter the network with their maximum allowed transmission rate. In this case, the network is congested and the obtained transmission rate ρ_i is significantly lower than the requested rate r_i. Thus, this price interval corresponds to a very inefficient network management, even though, as will be discussed in the following, the throughput might be high and hence the resource allocation seems to be effective. The region in which users adapt their requested rate to a higher price offers a more efficient coordination. In this case the revenue increases linearly at first (which means a constant throughput). Then, the effect of users leaving the service, considered too expensive, causes a throughput

Number of users	7	10	15	20
Throughput $\alpha = 0.04$	6.333	8.995	10.103	10.101
Max. revenue	0.255	0.361	0.468	0.518
Price of max. revenue	0.041	0.042	0.049	0.055

Tab. 2. Remarkable Values for Offered Load 1600 kbps per User

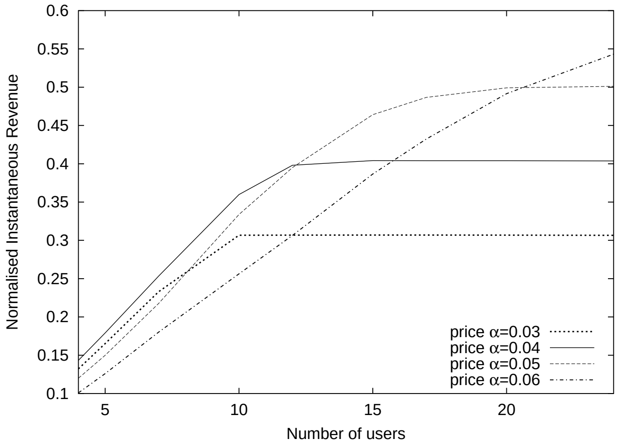

Fig. 3. Instantaneous normalised revenue for pricing $p(r_i) = \alpha r_i$ as a function of the number of users

decrease, so that the revenue still increases but less than linearly, until a maximum is reached. Finally, the revenue decreases as the number of users refusing the service is too high.

The most interesting values for each curve are reported in Table 2 for reference. We report the throughput obtained for unit price equal to 0.04, which according to Figure 1 represents a price which is still accepted by a fraction of users higher than 90%, though it causes a significant reduction of users' requested rate. It might be seen that for this price the capacity of the network is fully allocated only if the number of users is sufficiently large. On the other hand, the number of users which can achieve a QoS close to their requests decreases when the load is increased. Hence, there is a trade-off in the network dimension that the provider should expect to have a satisfactory management. On the one hand, with too low a load it is not easy to have full allocation of the resource, whereas on the other hand too many users can not achieve a QoS according to users' requests. Moreover, at high loads the allocation becomes inefficient for the provider if the price is too low, since the capacity would have been fully allocated even if a higher price had been set.

Also we report in Table 2 both the maximum revenue and the price value which gives such a revenue. As discussed before, the revenue is maximised when the price is considered acceptable by the users, i.e., neither too high nor too low. However, note that this price depends on the number of users in the network, so that its setup is not trivial. In real world a provider should thus establish a tariff plan differentiated according to the Time of Day which takes into account the expected number of customers.

In Figure 3 we represent again the revenue on the y-axis by plotting the number of users on the x-axis. One can expect that increasing the number of users generates additional revenue, but this depends on how the price is set. It can be observed that the revenue saturates when the load becomes high with respect to the price, so that the bottleneck is the amount of resource, not the users' acceptance. However, increasing the price causes higher saturation revenue but also poorer performance in the intermediate range of number of users.

The inefficiency of too high prices can also be seen in Figure 4, where, instead of the revenue, we plot the throughput $\sum_{i=1}^{N} \rho_i$. It is highlighted that the throughput comes to a saturation value close

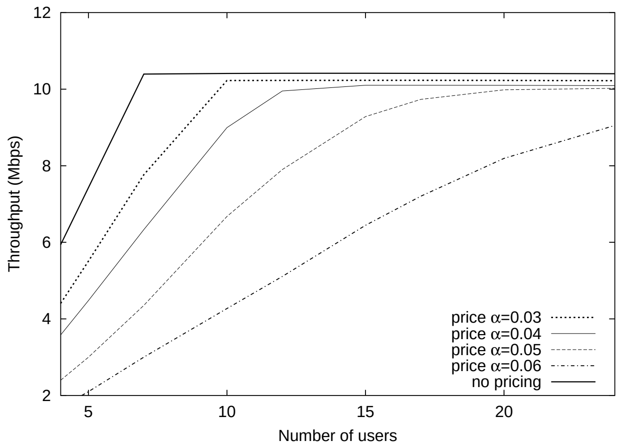

Fig. 4. Instantaneous throughput for pricing $p(r_i) = \alpha r_i$ as a function of the number of users

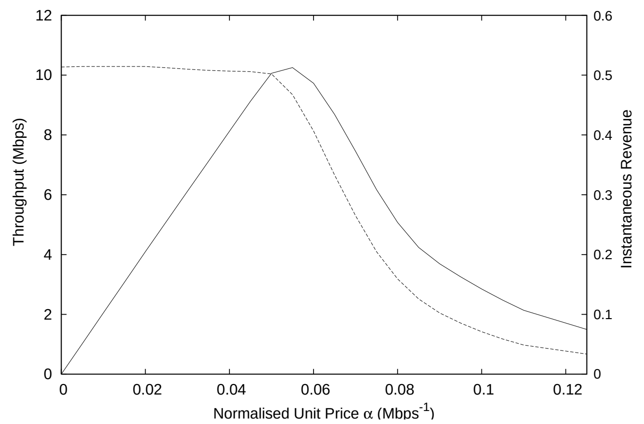

Fig. 5. Revenue and throughput for linear pricing as a function of the unit price

to $\mathcal{M}$; there is a loss due to the protocol overhead, which is always larger than 9% and increases as the price increases. Note also that the lower the price, the lower the point of saturation and the slope is also steeper. The *no pricing* case, reported for comparison, has an ideal behaviour which heavily changes when the number of users becomes greater than 7. Before this threshold value the throughput increases linearly, and saturates after to a constant value. However, the larger the price, the further the behaviour of the curve (which is smoother) from the ideal case. These phenomena can not be seen in Figure 3, since they are hidden by the fact that ultimately the higher the unit price α, the higher the revenue. However, network usage should also be considered as a measure of efficiency besides the revenue, so a careful design should consider both aspects jointly. In particular, a trade-off must be cut between having high revenue (which might be a short-term objective of the provider) and high throughput, which means efficient resource usage and thus good resource management on the long term.

A possible sum-up of the results is given by considering Figure 5, where 20 users in the WLAN hot-spot have been considered. The price per Mbps is reported on the x-axis, and both metrics have been considered, throughput and revenue.

In this way it is possible to identify the aforementioned trade-off. For example, low values of the price (see also Figure 4) allow to bring the total throughput above 10Mbps. This happens however since such a low price satisfy every user. Thus, the coordination among users in this case could even be very inefficient. In fact, due to low price, every user accepts even a low throughput. In general, the region in which users adapt their requested rate to the price offers a more efficient coordination, since the throughput is slightly decreased, but the revenue increases. In other words, revenue and throughput offers a good estimate of the management efficieny only if they are considered jointly, so that it can be understood if the management operation results in significant resource allocation and satisfactory revenue.

To summarise, Figures 2–5 can be seen as a guideline to set the price according to the expected number of potential users in the WLAN. However, it is emphasised how the tariff choice is not trivial, as first of all there are only small ranges in which a price value implies satisfactory revenue, and also there is a strong dependence on the CSMA/CA constraint which generates non-trivial effects.

IV. Conclusions and Future Works

The RRM task for a WLAN Hot-Spot is not trivial and involves several related issues. In particular, in this work we focused on the point-of-view of the provider's revenue. The goal of achieving satisfactory income is decomposed in the search for a good network efficiency and for a high appreciation by the users. To represent this aspect, we applied a micro-economic framework to depict users' choices in a decentralised way.

Results obtained by theoretical modelling and simulations show that the same system behaves differently when economic aspects like price and users' satisfaction functions are considered. Thus, the pricing policy has a heavy role for the correct evaluation of the system performance.

Moreover, it is at the same time true that pricing can tune the number of users in the system but also the estimated demand must be known to appropriately set up the price. Hence, there are tight inter-dependencies between pricing and efficiency of the protocol that our model allows to study and whose correct evaluation is useful not only for the provider's network planning, but also for the protocol efficiency that can be improved.

Possible developments of this work includes an *a posteriori* analysis in which the reaction of the users is considered in a dynamic way, i.e., by including resource renegotiation after the first round of assignments. Also the tariff strategy might be changed at a structural level: for example, variable pricing strategies and negotiations can be taken into account in order to let the provider optimise network management from both technical and economic point-of-view.

Acknowledgements

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