A price based load balancing scheme for multi-operator wireless access networks

Johnny Choque[†], Ramón Agüero[†], Joan Serrat[‡], and Luis Muñoz[†]

[†]Universidad de Cantabria, Santander, Spain
[‡]Universidad Politécnica de Catalunya, Barcelona, Spain
[†]{jchoque, ramon, luis}@tlmat.unican.es, [‡]serrat@tsc.upc.edu

Abstract. We study a load balancing strategy, based on the price offered by the base stations to the end-users who are willing to establish a connection. The proposed scheme is compared with a pure load balancing procedure, in a scenario comprising two different operators. We study the impact of modifying the price offered by the base stations, in terms of the achieved load balancing, as well as considering the revenue obtained by the operators. Furthermore, we also enhance the two former access selection schemes, by incorporating the willingness of reducing the number of handovers, so as to analyze the impact over this particular parameter, and over all the previous results. The whole work is conducted over a proprietary event-based simulation tool, which offers the required degree of flexibility and low computational overhead.

1 Introduction

It is now foreseen that the upcoming future of wireless communications will be characterized by a wide range of network alternatives, managed by a relatively large number of operators, allowing the user to use a vast set of services, with different quality of service (QoS) and price levels. This, together with the recent proliferation of devices and gadgets equipped with various technologies, brings about new challenges and opportunities. From the perspective of the operators, they would also need strategies so as to optimize the use of their deployed infrastructure, not only at the high-load (peak traffic) situations, but also when the demand is low, with the main goal of maximizing their revenues, while keeping the service level agreements with the end-users.

It is now also believed that in this scenario the end-user would increase her responsibility degree within the decision process. In this sense, she would select those access alternatives which better suits her needs, on the basis of a number of different parameters and her own preferences. In spite of the effort which has been put by the wireless research community on some of these parameters, most of the existing works focus on network conditions and the related physical parameters. It can be also argued that other aspects, e.g. the price, might also play a fundamental role in determining the satisfaction level of the end-user when she accesses any service. Besides, it goes without saying that price also appears as a fundamental parameter for the operators, allowing them to define strategies so as to increase their benefits.

This work proposes a dynamic price scheme aimed at achieving load balancing between base stations, which might belong to the same or different operators. The end-user would consider additional merit parameters (mostly related to the wireless realm we are tackling) to choose the base station to connect to, establishing different access selection strategies, which are later compared.

The paper is structured as follows. Section 2 discusses related work on price strategies, positioning the presented approach against other proposals. Section 3 depicts the price-based load balancing and the corresponding access selection strategies, which will be challenged in the scenario introduced in Section 4, which also describes the tool which has been used to conduct the analysis. Results are discussed in Section 5, while the paper is concluded in Section 6, which also advocates some items which are left for future work.

2 Related Work

There exist a number of works which have proposed the integration of pricing concepts to enhance access selection algorithms or as a way to develop strategies to maximize operator revenues, while keeping end-user satisfaction levels.

On the first hand, we can identify a first group of works in which price is part of the access selection algorithms. Amongst these, it is worth highlighting the schemes based on *game theory*, which appears as one of the most used tools when evaluating the best access alternatives to be selected by the end-user. In the work by Niyato *et al.* [9], users compete for the resources offered by the various wireless networks based on a utility function which depends on the requested bandwidth and the connection price. Besides, the authors do not aim at fostering load balancing between the involved networks, which might lead to a degradation of the offered *QoS*, if some of the base stations gets overloaded. In this sense, *game theory* can be also used so as to specifically address load balancing; for instance, the authors in [1] tackle this problem, by setting out a game where the base stations (*players*) aim at providing a more *social* behavior (thus leading to a certain load balancing), rather than seeking their own benefit.

On the other hand, price-based load balancing has been frequently used in fixed networks (see e.g. [7, 8]); in this case several price policies are proposed so as to get the most appropriate QoS and load balancing. A drawback of these approaches is that, since they target fixed networks, the corresponding algorithms do not consider parameters which are intrinsic to wireless networks (e.g. handover). In this sense, to our best knowledge, there are not many works in the related state of the art whose main goal is load balancing based on price policies for wireless networking scenarios. Some studies ([6, 11]) focus on load balancing over wireless networks, but they do not use price in the proposed algorithms. Furthermore, the proposals made in [3, 10] include price within the access selection schemes, albeit their goal is not fostering load balancing between the base stations.

One proposal which is close to the approach we follow in this work is the one by Falowo *et al.* [5]. They define various service classes, whose prices are updated based on the residual available capacity of each of the access elements, establishing the maximum admissible rate to achieve the required load balancing. In order to ensure that operator's revenue does not decrease to unacceptable levels, the price per service is maintained between some predefined thresholds. As opposed to this latter work, we consider a multi-operator scenario, where novel players might have different strategies so as to attract users, and thus obtain a higher revenue.

3 Load Balancing Strategies

One of the main goals of this work is to analyze whether the operators might be able to use their pricing strategies so as to reach an appropriate load balancing between the deployed access elements. We would assume that end-users should be able to access the available services on an automatic and transparent way, without being limited by technological or administrative (operator-based) barriers, and that base stations would modulate the offered price with the instantaneous load, so that they can encourage or deter users from connecting depending on the current available capacity. It is worth highlighting that we are assuming that the end-users are not subscribed to either of operators involved in the analysis and therefore they do not have any preference towards any of them. As such, we can describe the scenario as an open market, where the costumers select the alternative that offers the best overall utility.

In order to establish the price, we propose a piecewise function, as depicted in Figure 1. In this sense, each of the access elements would use two thresholds. When the available capacity is below Lth_{lower} value, the access element set its price to the maximum ($p_{\max}$), so that to deter the end-user to connect to a highly loaded base station; if it is above Lth_{upper} value, the base station sets its price to a minimum acceptable one, $p_{\min}$ ($p_{\min} = \psi \cdot p_{\max}$, with $\psi \in \langle 0, 1]$), since the goal would be to 'quickly' convince the end-user to change to a low loaded base station. Otherwise, a linear decreasing function is used, by means of which the price is modulated with the currently carried load. In this sense, if the relative load of a certain base station j was θ_j (i.e. its available relative capacity equals $1 - \theta_j$), it would fix a price p_j, as can be seen in Figure 1.

For the sake of generality, we assume that, in order to select the most appropriate access network, an end-user detects the set of available alternatives, those which are within her coverage range, and sorts them based on a weighted linear function, which can be tuned so as to consider various criteria. This approach is rather generic and flexible and therefore it can be tailored so as to implement a wide range of decision strategies. In particular, all of the detected access elements are given a *total score*, by using:

$$\Phi_i = \sum_{j=1}^{N} \omega_j f_{ij} \tag{1}$$

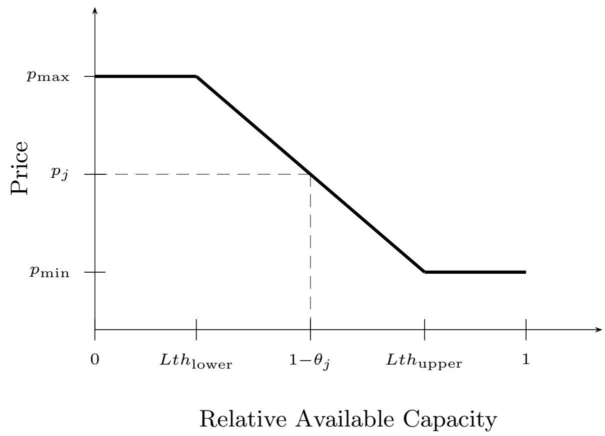


Fig. 1. Base station price as a function of current load

where Φ_i is the multi-criteria (aggregate) utility of access element i, ω_j is the weight of the j^{th} criterion and f_{ij} is the value of the utility function of each of the N criteria, as perceived by end-user if she connected to access element i. Finally, the end-user selects the access alternative with the highest score, amongst those with enough capacity to handle the current service request.

In [4], we presented a similar approach and we introduced a number of potential figures of merit. All of them were modeled so as to get a value between 0 and 1, so by fixing $\sum_{j=1}^{N} \omega_j = 1$ we could bound Φ_i within the same interval. We used criteria such as link quality, preferred operator, minimization of handovers and load. In the framework of this work, we will use three different criteria, which are briefly discussed below.

3.1 Price criterion

The goal of this criterion is to analyze the feasibility of using price as a means to deter or encourage end-users to select a particular access alternative. From the perspective of the operator, this would avoid saturating some base stations, promoting the selection of less loaded alternatives. In this sense, we need to include the offered price as another parameter to be considered during the access selection procedure. With that idea in mind, we proposed in [4] a triangular function; this has the disadvantage that the same absolute variation on the price leads to the same change on the utility function, as opposed to a more sensible approach, in which end-users would compare access alternatives based on the relative difference between various prices. In order to overcome this limitation, we have opted for a logarithmic function within this work, so as the offered price (p_i), which is within $p_{\min}$ and $p_{\max}$,[1] gets a fair score in Eq. 1. Hence, the price utility function A_i is defined as follows:

[1] As can be seen in Figure 1, the offered price can vary within such interval.

$$\mathrm{A}_i = -log\,(p_i) \quad p_{\min} \leq p_i \leq p_{\max} \tag{2}$$

3.2 Handover criterion

From the perspective of the end-user it might seem very attractive to always select the cheapest access alternative (thus taking decisions solely based on such criterion); however, it is well know that changing base stations may also bring about some overhead and QoS degradation. In this sense, the end-user might be also tempted on maintaning the current base station as much as possible[2]. It is worth highlighting that this criterion does not actually force the user to necessarily keep the same base station, but it adds an additional value (σ) to the overall utility, when the current access alternative (i) is the one the end-user was previously connected to (BS_i). This way, we define the handover utility function B_i as:

$$\mathrm{B}_i = \begin{cases} \sigma & \text{if end-user was connected to } BS_i \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

3.3 Load criterion

This is possibly one of the aspects most favored by the network; the goal here is to balance the load of the various base stations without taking into consideration the particular operator they belong to. On a similar way that the price criterion, in [4] we also proposed a triangular function to modulate the price based on curent load; in the framework of this work we also consider the operator willingness to encourage or deter the user from using a particular base station, considering the load it is currently carrying. The goal is to offer the user a higher utility when, being connected to a more loaded base station, she tries to change to another one and, likewise, when the current base station is low loaded, to give a lower utility so as to encourage her to maintain the same connection. In order to model this behavior we use a potential function. If we define l_i as the current relative load, we define the load utility function Γ_i as:

$$\Gamma_i = 1 - l_i^2 \quad 0 \leq l_i \leq 1 \tag{4}$$

3.4 Access selection strategies

In general, taking into account the previous discussions, the multi-criteria utility function (Φ_i) can be expressed as follows.

[2] We assume that while a service is being run, the end-user periodically senses her environment so as to check whether a better access alternative is available, even before she gets close to the coverage bound of the current base station.

Strategy	α	β	γ
Price Based Load Balancing (PBLB)	1.0	0.0	0.0
Enhanced PBLB (ePBLB)	0.5	0.5	0.0
Load Balancing (LB)	0.0	0.0	1.0
Enhanced LB (eLB)	0.0	0.5	0.5

Table 1. Access selection strategies

$$\Phi_i = \alpha \cdot \mathrm{A}_i + \beta \cdot \mathrm{B}_i + \gamma \cdot \Gamma_i \tag{5}$$

where α, β and γ are the weights give to the price, handover and load criteria, respectively, and we force them to sum up to 1.0.

By selecting different values for these weights, we can establish the access selection strategies which are depicted in Table 1. Since the pure *Load Balancing* (LB) strategy just favors load balancing, the goal is to compare the results with those assessed with the proposed *Price Based Load Balancing* (PBLB), which only favors the price parameter. The two enhanced versions (eLB and ePBLB) are used in order to analyze the tradeoff between reducing the number of handovers and achieving a better load balancing.

3.5 Price and handover criteria relationship

Assuming that the operator wants to establish a strategy based on price and handover criteria, we will derive the σ value, which was previously defined (see Eq. 3), so as to avoid that neither of the two criteria has a stronger impact within the overall utility. In order to do so, we force the corresponding weights (see Eq. 1) to equal ω, as shown below.

$$\Phi_i = \omega \cdot \mathrm{A}_i + \omega \cdot \mathrm{B}_i \tag{6}$$

In this sense, lets consider that an end-user is connected to a certain BS_a, paying a price P_a, and we would like to analyze the possibility of changing to another BS_b, since it offers a cheaper price. In particular, the price of the second BS has a reduction of χ $(100 \cdot \chi\%)$ over the one offered by the current active one $P_b = (1 - \chi) \cdot P_a$. Evaluating expression (6) at BS_a we can obtain:

$$\Phi_a = \omega \cdot (-log\,(P_a)) + \omega \cdot \sigma_P \tag{7}$$

Likewise, for BS_b, since it implies a handover from BS_a, we can write:

$$\Phi_b = \omega \cdot (-log\,(P_b)) \tag{8}$$

If we take the limit situation, and we make both scores equal, so as to establish the σ_P value which would lead to a handover situation, yielding that $\sigma_P = -log\,(1 - \chi)$. As a design decision, we will assume that an end-user would change the access alternative when it is 20% cheaper than the current one ($\chi = 0.20$). By substituting in the aformention expression, we obtain that σ_P equals 0.10.

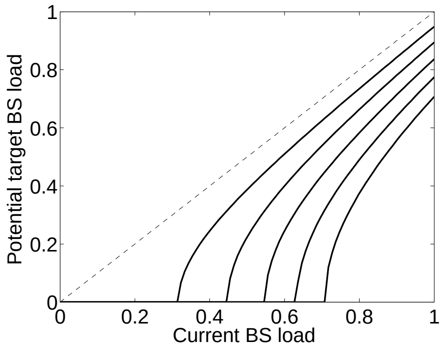


Fig. 2. Load hyperbolic function

3.6 Load and handover criteria relationship

In this case, we assume that the operator wants to use a strategy based only on load and handover criteria. Following a similar analysis than the one which was previously carried out, when the end-user is connected to a certain BS_a, whose current relative load is L_a, the corresponding utility can be obtained as follows:

$$\Phi_a = \omega \cdot \sigma_L + \omega \cdot \left(1 - L_a^2\right) \tag{9}$$

Besides, for BS_b, since it implies a handover from BS_a, we can write:

$$\Phi_b = \omega \cdot \left(1 - L_b^2\right) \tag{10}$$

When both Φ_a and Φ_b are the same value (limit situation) we can write an hyperbola equation, as can be seen below.

$$\frac{L_a^2}{\sigma_L} - \frac{L_b^2}{\sigma_L} = 1 \tag{11}$$

Figure 2 shows the curves which are obtained for different σ_L values (from 0.1 to 0.5). These establish the areas (considering the loads of two base stations, the current one and another potential destination) in which the end-user would take the decision of changing her access. In this sense, all combinations below a particular curve would make the end-user to change to the other base station. The straight line ($\sigma_L = 0$) can be seen as the limit (when handover is not considered within the utility function). Since its behavior is sensible we have selected (as a design parameter) that $\sigma_L = 0.1$.

4 Simulator and Scenario

In order to evaluate the strategies proposed in the previous section, we have used the proprietary simulator *multi-Constraint Access Selection in heterogeneous Environments (mCASE)*, whose architecture and detailed operation were discussed in [4]. *mCASE* uses a discrete capacity unit, the so called *Traffic Unit*

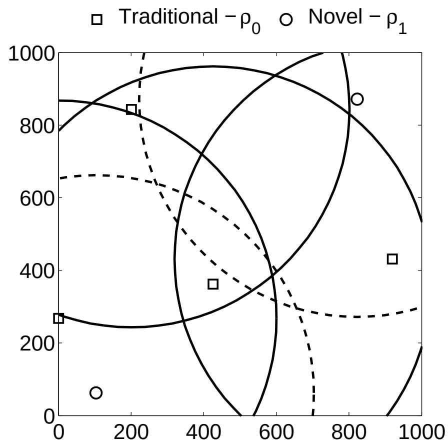


Fig. 3. Network deployment used during the analysis

Operator	ID	Coverage (m)	Capacity (TUs)	# Base Stations
Traditional	ρ_0	600	20	4
Novel	ρ_1	600	20	2

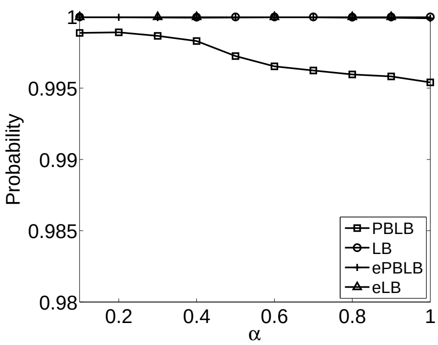
Table 2. Involved technologies

(TU), which affects both the capacity required by the different services which are started by the end-users as well as the capacity of the different access elements.

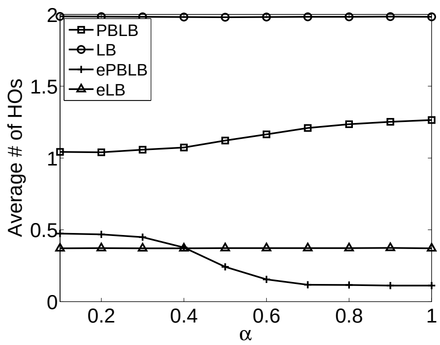
The analysis will be carried out over a scenario comprising a number of base stations of a single technology (mimicking a legacy cellular deployment), as depicted in Table 2. We further assume that there exist two operators; the first one might be matched to a traditional operator, with a slightly larger deployment (in terms of the number of base stations), while the second one might resemble a novel operator which tries to get market share with a more aggresive price strategy, albeit having a smaller infrastructure. In addition, we consider a square area of 1000 m side, in which the base stations are deployed without any particular previous planning (although limiting the minimum distance between them, when they belong to the same operator). The particular network deployment which will be analyzed is shown in Figure 3.

250 users are randomly deployed within the same area and afterwards they move following a Random Waypoint model [2], with a *pedestrian* speed, randomly selected within the interval $[1, 3]$ (m/s). Each of the end-users would start services by means of an *ON-OFF* model in which both the inter-arrival and service times are modeled with negative exponential random variables, with means 120 and 60 seconds, respectively. We assume that the required capacity for the services requested by the end-users equals 1 TU.

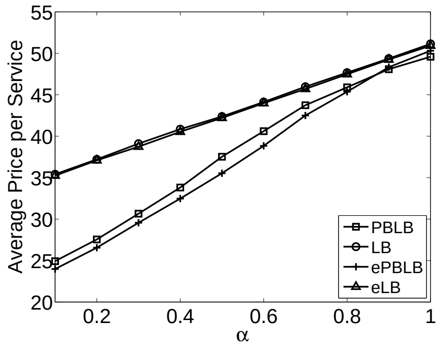
We also define a generic monetary unit, as the amount of money a end-user needs to pay per TU and per second. Since the service we are using in this work requires 1 TU (as was discussed in the above paragraph), a particular call of x



(a) Successful services



(b) Handovers



(c) Service price

Fig. 4. Access selection strategies performance from user point of view

seconds would have a cost of $x \cdot p$, where p is the current price (in the defined monetary units) offered by the selected base station.

5 Discussion of results

In this section we describe the results which were obtained when using the four access selection strategies which have been presented in Table 1. All the simulation runs last 3600 seconds, and 100 independent executions are carried out per case, so as to ensure the statistical validity of the results. These can be grouped according to whether they affect more the end-user or the network operators. Figure 4 focuses on these parameters which allow getting an idea on the performance perceived by the end-users, while Figure 5 shows a set of results which can be used to yield the benefits that the various strategies might bring about to the two operators.

We assume that the traditional operator does not change its price/capacity function, but we vary the maximum price of the novel operator, as a percentage of the one used by the traditional operator. In this sense, we define the price factor (α) as:

$$\alpha = \frac{(p_{\max})_{\text{novel}}}{(p_{\max})_{\text{traditional}}} \tag{12}$$

In particular, we increase α from 0.1 (where the maximum price of the novel operator is 10% of the traditional one) to 1.0, where the two operators use the same price strategy, as showed in Figure 1[3].

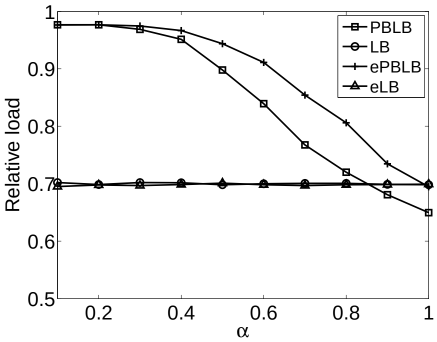
First of all, Figure 4(a) shows the probability for any call to be successful. The first conclusion is that this parameter is not highly affected by the value of α, since the successful probability remains stable for all α values, showing (for all cases) a rather appropriate behavior (≥ 0.995). PBLB appears as the only case which slightly goes away the optimum performance assessed with the rest of strategies, although the decrease is almost negligible (0.5%). Therefore, with the parameters of this particular network deployment, the call failure probability is, for all cases, rather low, thus showing an acceptable *QoS* for all the strategies.

In the two *enhanced* versions of the load balancing access selection strategies, we included the minimization of handovers as another criterion to be considered in the multi-criteria utility function. In order to analyze its effect, Figure 4(b) shows the average number of handovers which were required per call. As can be seen, the figure does not show a relevant influence of α over this parameter, as it also happened with the successful call probability. However, in this case, the figure yields a clear difference between the various strategies. In the LB, the number of handovers per call stays around 2.0, which somehow can reflect a *ping-pong* effect, consequence of the load balancing goal. When reduction of handovers is considered in the multi-criteria utility function (eLB), the impact appears very clearly, as the number of handovers per call is reduced to around 0.4. Regarding the PBLB, we can see that the average number of handovers is slightly above 1.0, which gets reduced to below 0.5 when the reduction of handovers is considered in the multi-criteria utility function (ePBLB).

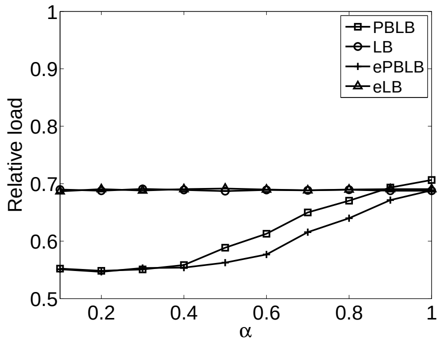
Opposed to the two previous parameters, we might have expect that the average price per call, which is shown in Figure 4(c), would be influenced by the α parameter, since it gathers the price the novel operator is charging for accessing its base stations. The increase for those strategies which do not consider price (LB and eLB) follows a linear trend, being both of them alike. For the two strategies which consider price (PBLB, ePBLB), service price is clearly affected by the α parameter. In this case, the strategy which leads to the cheapest prices is the ePBLB, while the strategy which only favors the price criterion (PBLB) leads to a slightly higher service price.

With respect to the parameters which reflect the performance from the operator perspective, Figures 5(a) and 5(b) show the relative load (ratio between the used and the available resources), while Figures 5(c) and 5(d) correspond to the revenue that the two operators get from each of their deployed base stations. In the case of the two strategies which do not consider price (LB, eLB), load does not get affected by the α parameter and, as can be seen, they both reach an almost ideal load balancing (relative loads are more or less the same for

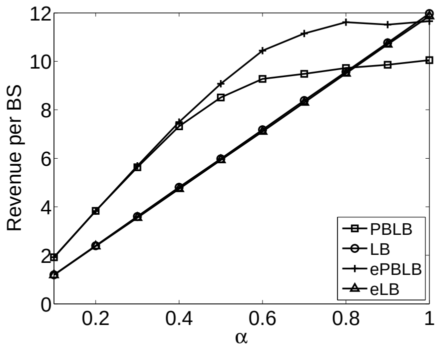
[3] In all cases, $p_{\max}$ for the traditional operator was set to 1.0 monetary units.



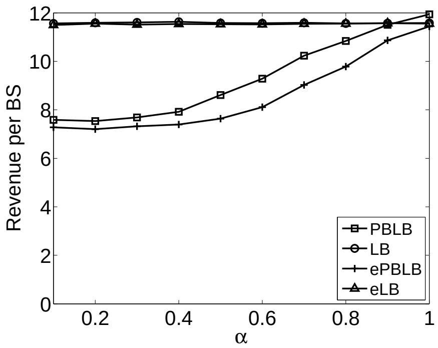
(a) Novel operator load



(b) Traditional operator load



(c) Novel operator revenue



(d) Traditional operator revenue

Fig. 5. Access selection strategies performance from operator point of view

both operators). However, for the two other strategies (PBLB and ePBLB) the results yield a tight relationship with the α parameter. In this sense, when the novel operator is offering cheap prices (i.e. α is small), the relative load of the traditional operator is quite low (< 0.6), while it reaches values close to 0.95 for the novel operator. Furthermore, as α increases, the relative load of the novel operator gets lower, augmenting for the traditional one. This effect could have been expected, since an increase in α really means that the prices offered by the novel operator are closer to the traditional operator ones. It is worth saying that when α is high (> 0.9), the results (in terms of load balancing) equals the ones achieved with the pure load balancing strategies.

Finally, it could be argued that the most relevant results are those related with the revenue obtained by the operators. It is worth recalling that the price strategy of the traditional operator is the same for all α values ($p_{\max} = 1.0$) and, therefore, for those two access selection methods which do not consider price (LB, eLB), its revenue does not change with α; however, for the novel operator, we can see (for these two strategies) a linear increase, which corresponds to the same trend in the maximum price used by the corresponding base stations. On the other hand, when price is considered within the access selection strategy (PBLB and ePBLB), there is a clear impact on the two operators' revenue. For the traditional one, the revenue always increases with α; the reason is that the more expensive the novel operator is, the more end-users would select the traditional alternative (as it was also reflected in the load results - see Figure 5(b)). Besides, Figure 5(c) yields that the novel operator does not perceive significant additional gain when $\alpha > 0.7$; in this case there is a tradeoff between the reduction of the load and the price users are paying. Furthermore, when users try to keep the same base station as much as possible (introducing handover reduction in the access selection strategy, ePBLB) we can see how the novel operator obtains some additional benefit, as opposed to the traditional one (this is only relevant when α is higher than 0.6).

6 Conclusions

This paper has analyzed a load balancing scheme, based on the price offered by the base stations, which adjust it according to their current available capacity so as to deter or encourage more users to connect to them. We have shown that, only with the information about the connected users, the proposed method offers a good performance, compared to a pure load balancing strategy. A scenario comprising two operators (both traditional and incumbent/novel) has been used. We have studied the impact of establishing different prices for the case of the novel operator, as opposed to the traditional one, whose pricing policies have always remained the same. We have also analyzed the impact of such variation on the revenues obtained by the two operators, as well as on the goodness of the achieved load balancing. The results yield that the load of the novel operator is higher as its offered prices are cheaper, but this does not however lead to the maximum revenues.

All the analysis have been conducted over a proprietary event-based simulator tool, which, thanks to its flexibility and low computational overhead, has allowed the execution of a large number of independent runs, ensuring the statistical validity of the results. In addition, the two former strategies were also enhanced, by introducing another parameter of merit during the access selection procedure. In this sense, the results proved that incorporating a certain willingness to reduce the number of handovers was very effective.

The proposed mechanism and the employed tool have been both conceived with the idea of allowing a wider range of studies. We will, for instance, study how different types of users (i.e. business), who are willing to pay more for having a better service can also benefit from the proposed pricing strategy. In addition, we will also incorporate more parameters in the access selection procedure, like the preference to connect to a certain operator, and the penalization which base stations would impose to those end-users who do not have an agreement with the corresponding operator. The analysis will be also enriched by considering heterogeneous technologies.

Acknowledgements

The authors would like to express their gratitude to the Spanish government for its funding in the following project: "Cognitive, Cooperative Communications and autonomous SErvice Management", C3SEM (TEC2009-14598-C02-01). Ramón Agüero and Luis Muñoz would also like to thank the European Commission for its funding through the "Scalable and Adaptive Internet Solutions", SAIL Project (FP7-ICT-2009-5-257448)

References

1. Awada, A., Wegmann, B., Viering, I., Klein, A.: A game-theoretic approach to load balancing in cellular radio networks. In: Personal Indoor and Mobile Radio Communications (PIMRC), 2010 IEEE 21st International Symposium on. pp. 1184 –1189 (sept 2010)
2. Bettstetter, C., Resta, G., Santi, P.: The node distribution of the random waypoint mobility model for wireless ad hoc networks. Mobile Computing, IEEE Transactions on 2(3), 257 – 269 (sep 2003)
3. Chan, H., Fan, P., Cao, Z.: A utility-based network selection scheme for multiple services in heterogeneous networks. In: Wireless Networks, Communications and Mobile Computing, 2005 International Conference on. vol. 2, pp. 1175 – 1180 vol.2 (june 2005)
4. Choque, J., Agüero, R., Muñoz, L.: Simulation framework for the evaluation of access selection algorithms over heterogeneous wireless networks. In: 3rd International ICST Conference on Mobile Networks and Management (MONAMI'2011) (September 2011)
5. Falowo, O.E., Zeadally, S., Chan, H.A.: Dynamic pricing for load-balancing in user-centric joint call admission control of next-generation wireless networks. Int. J. Commun. Syst. 23, 335–368 (March 2010)
6. Gelabert, X., Pérez-Romero, J., Sallent, O., Agustí, R.: On the suitability of load balancing principles in heterogeneous wireless access networks. In: Wireless Personal Multimedia Communications (WPMC), 2005 Second International Symposium on (sept 2005)
7. Gu, C., Zhuang, S., Sun, Y., Liu, C., Sun, N.: Pricing incentive mechanism supporting load balancing for QoS-enabled networks. In: Biomedical Engineering and Computer Science (ICBECS), 2010 International Conference on. pp. 1 –4 (april 2010)
8. Liou, B.S.: Quality of service pricing network architecture supporting load balancing. In: Ubi-Media Computing, 2008 First IEEE International Conference on. pp. 503 –507 (31 2008-aug 1 2008)
9. Niyato, D., Hossain, E.: Dynamics of network selection in heterogeneous wireless networks: An evolutionary game approach. Vehicular Technology, IEEE Transactions on 58(4), 2008 –2017 (may 2009)
10. Piqueras, R., Pérez-Romero, J., Salient, O., Agustí, R.: Dynamic pricing for decentralised RAT selection in heterogeneous scenarios. In: Personal, Indoor and Mobile Radio Communications, 2006 IEEE 17th International Symposium on. pp. 1 –5 (sept 2006)
11. Song, W., Zhuang, W., Cheng, Y.: Load balancing for cellular/WLAN integrated networks. Network, IEEE 21(1), 27 –33 (jan-feb 2007)