Rate Adaptive Resource Allocation and Utility-Based Packet Scheduling in Multicarrier Systems

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ABSTRACT:
There are several approaches for Radio Resource Management (RRM) in multicarrier cellular systems. This work analyzes and compares two of them: rate-adaptive resource allocation (sub-carriers and power) based on instantaneous data rates, and utility-based packet scheduling based on average data rates. A fundamental RRM problem in wireless cellular networks was chosen as a background to evaluate the aforementioned approaches: the trade-off between system spectral efficiency and fairness among the users when opportunistic allocation is used. Extensive system-level simulations were performed and important network metrics such as total cell throughput, mean user throughput, system fairness index and user satisfaction were assessed. It was concluded from the simulation results that it is possible to achieve an efficient trade-off between resource efficiency and fairness using any of the two RRM approaches. However, utility-based packet scheduling algorithms based on average data rates have the advantage of presenting higher user satisfaction with less computational complexity.

KEYWORDS: Sub-carrier assignment, power allocation, packet scheduling, rate adaptive, utility theory, OFDMA.

1. INTRODUCTION

The wireless shared channel in cellular networks is a medium over which many Mobile Terminals (MTs) compete for resources. In such a scenario, resource efficiency and user fairness are crucial aspects for resource allocation.

From a cellular operator perspective, it is very important to use the limited radio resources efficiently in order to maximize the revenue. From the users' point of view, it is more important to have a fair resource allocation so that they can meet their Quality of Service (QoS) requirements and maximize their satisfaction.

The time-varying nature of the wireless environment, coupled with different channel conditions for different MTs, poses significant challenges to accomplishing these goals. In general, these objectives cannot be achieved simultaneously and an efficient trade-off must be achieved. In recent years Radio Resource Management (RRM) has been envisaged as one of the most efficient techniques to achieve a desirable trade-off among these two conflicting objectives in cellular multi-carrier systems.

On the other hand, several next generation wireless systems are based on Orthogonal Frequency Division Multiple Access (OFDMA), which provides a high degree of flexibility that can be exploited by RRM algorithms. There are different sources of diversity in an OFDMA-based system, such as time, frequency and multi-user diversities. Many Radio Resource Allocation (RRA) algorithms have been proposed to take advantage of these kinds of diversity, such as Dynamic Sub-carrier Assignment (DSA), Adaptive Power Allocation (APA), and adaptation of the Modulation and Coding Scheme (MCS) according to the instantaneous channel conditions (bit loading). Furthermore, Packet Scheduling (PSC) algorithms are responsible for deciding when the MTs will access the shared channel and with which transport format depending on the Channel State Information (CSI).

A significant number of separate or joint RRA solutions including DSA, APA and bit loading were based on combinatorial optimization. Most of the works in literature follow either the *margin adaptive* approach, which was initially proposed by [1] and formulates the dynamic resource allocation with the

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goal of minimizing the transmitted power with a rate constraint for each user [2], or the *rate adaptive* approach aiming at maximizing the rate with a power constraint [3, 4, 5].

On the other hand, many works have been using Utility Theory to propose solutions for all the aforementioned RRA algorithms, including also multi-carrier PSC. The issues of efficiency, fairness and satisfaction of resource allocation have been well studied in economics, where utility functions are used to quantify the level of customers' satisfaction when the system allocates certain resources to them. Utility theory performs the optimization of a utility-pricing system, which is established based on the mapping of some performance criteria (e.g. rate, delay) or resource usage (e.g. sub-carriers, power) into the corresponding pricing values [6, 7].

In this work, we will focus on the provision of Non-Real Time (NRT) services, such as World Wide Web (WWW) browsing, File Transfer Protocol (FTP) and e-mail. For these kind of services, the data rate is the most important QoS metric. The optimization problem can be formulated based on instantaneous or average data rates. The former case is stricter because QoS and fairness has to be guaranteed in each Transmission Time Interval (TTI), while the time window considered in the optimization problem based on average data rates adds a time diversity that relax the requirements on QoS and fairness.

The present work will be divided in two parts. In the first part, we will study rate adaptive sub-carrier and power allocation using optimization based on instantaneous data rates. In the second part, we will study multi-carrier packet scheduling using utility functions based on average data rates. The objective of the paper is to study the trade-off between resource efficiency and fairness among the users when the RRM algorithms mentioned above are used.

The paper is organized as follows. Section 2 presents the state-of-the-art revision while section 3 describes the system model. Sections 4.1 and 4.2 present the mathematical formulation of the rate adaptive resource allocation based on instantaneous data rate and the packet scheduling based on utility theory and average data rates, respectively. The simulation results are depicted in Section 5, while the conclusions are drawn in Section 6.

2. RELATED WORK

The objective of this work is to evaluate the trade-off between system resource efficiency and user fairness when using rate adaptive resource allocation or utility-based PSC algorithms. In order to do that, first of all the concept of fairness must be properly clarified.

There are two main fairness definitions: resource or QoS-based [8]. In the former, fairness is related to the opportunity to use network resources, e.g. amount of time during which a MT is permitted to transmit. In the latter, fairness is associated with the utility derived from the network, e.g. flow throughput. In the present work, the assumed concept of fairness is based on QoS. QoS-based fairness is related to the notion of how similar is the QoS experienced by the flows. If all flows in a given instant perceive more or less the same QoS level, we can say that the system provides a high fairness. On the contrary, if few flows experience a very good QoS while the others are unsatisfied, the resource allocation can be considered unfair.

Fig. 1 depicts a conceptual view of the trade-off between resource efficiency and QoS-based user fairness in a simplified scenario of two users in a wireless system. The axes present the QoS experienced by the two users after the resource allocation. One can notice that there are two main lines on the figure: fairness and efficiency. The fairness line indicates that the QoS of the users are the same in any point along this line, i.e. the fairness is maximum. Since the radio resources in the wireless system are limited, the efficiency line delimits a capacity region. The crossing between these lines is the optimal network operation point, which characterizes a resource allocation with maximum efficiency and fairness. In the figure, one can see regions of low, intermediate and high fairness and efficiency. Wired networks can effectively work near the optimal point due to the implementation of congestion control techniques, such as Transport Control Protocol (TCP) [9]. However, the frequency and time-varying wireless channel poses significant challenges to the solution of this problem, and the optimal RRA technique that always provides maximum efficiency and fairness in wireless networks is still an open problem. In fact, most of the times the optimal point may be unfeasible due to the channel quality of the users.

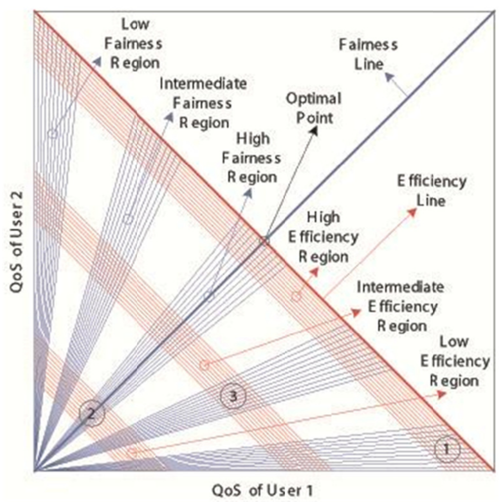

Fig. 1. Trade-off between resource efficiency and QoS-based fairness in wireless networks.

In order to illustrate that, a scenario is considered where user 1 has better channel conditions than user 2. Region 1 would be the result of an opportunistic RRA policy that gave importance only to the efficiency in the resource usage. In the considered scenario, the majority of the resources were allocated to user 1, while user 2 would starve, causing an unfair situation. On the other hand, region 2 characterizes an RRA policy that provides absolute fairness but causes a significant loss in efficiency since it has to deal with the bad channel conditions of user 2. Finally, region 3 is an example of how an RRA policy can balance these two opposing factors.

The compromise between efficiency and fairness was conceptually studied in [9, 10, 11, 12]. Among the works that have proposed RRA algorithms to cope with this trade-off in a NRT scenario, three main approaches can be highlighted: optimization-based rate adaptive resource allocation [4, 5, 13, 14, 15, 16, 17], cross-layer PSC [18, 19, 20, 21, 22, 23, 24, 25] and utility theory-based resource allocation [26, 27, 28, 29, 30, 31, 32, 6, 7, 33].

Among the rate adaptive-based papers, the notion of fairness criteria was determined by maximization of minimum user rate [4], proportional rate constraints [5, 13, 14, 15], or the maximization of the sum of the logarithm of user rates [16, 17]. The logarithm function was used in [16, 17] because it was proved in [26] that this function is intimately associated with the concept of proportional fairness.

Most of the works that proposed PSC algorithms to effect a compromise between efficiency and fairness among NRT flows, for example [18, 19, 20, 21] are based on the Proportional Fairness (PF) PSC algorithm proposed in [34] for High Data Rate (HDR) Code-Division Multiple Access (CDMA) systems.

However, there are some works like [22, 23] that used different approaches. The former introduced a PSC algorithm with a fairness controlling parameter that accounts for any intermediate policy between the instantaneous throughput fairness and the opportunistic policies, while the latter evaluated a scheduling algorithm whose priority function is a linear combination between instantaneous channel capacity and the average throughput. As a generalization of the PF criterion, we can highlight the weighted α-proportional fairness PSC algorithm, which is also known as the alpha-rule and was initially proposed by [24] and later used in [25]. The idea behind this algorithm is to embody a number of fairness concepts, such as rate maximization, proportional fairness and max-min fairness, by varying the values of parameter α and the weight parameter.

A more general class of RRA algorithms is based on utility fairness. Utility fairness is defined with a utility function that composes the optimization problem, where the objective is to find a feasible resource allocation that maximizes the utility function specific to the fairness concept used. Some examples of utility functions can be found in [26, 27, 28]. There is a general family of utility functions that were presented and/or evaluated in [29, 30, 31, 32] that includes the weighted α-proportional fairness algorithm as a special case.

In this paper, the derived RRA policy will be called utility-based alpha-rule. Some works followed a similar approach, but using utility functions that did not suit the utility-based alpha-rule exactly, e.g. [6, 7, 33]. To the best of our knowledge, the present work is the first one to make an explicit comparison between rate adaptive RRA algorithms based on instantaneous data rates and utility-based RRA algorithms based on average data rates regarding the trade-off between resource efficiency and user fairness in opportunistic wireless networks.

3. SYSTEM MODEL

The considered scenario is a single cell with hexagonal shape. We consider a network with one transmitter (base-station) and M receivers (mobile terminals). The transmitted Orthogonal Frequency Division Multiplexing (OFDM) signal is time-slotted, where in every time slot at most one user can be served over each sub-carrier. The considered environment is Typical Urban (TU) [35] where each user experiences independent transmit conditions. The channel is a frequency-selective Rayleigh fading channel, with the coherence time such that each sub-carrier experiences only flat fading. It is assumed that the channel fading rate is slow enough so that the frequency response does not change during a TTI interval. Each user also experiences shadowing with log-normal distribution. A perfect knowledge of the CSI at the transmitter side is assumed, with no signaling overhead transmitted. The signal strength at the receiver side depends on the pathloss calculated by:

$$L = 128.1 + 37.6\log_{10} d \tag{1}$$

where d is the distance to the base station in km.

The bit allocation on each sub-carrier is determined using the Shannon's capacity model shown in (2) below [6, 7]:

$$c_{j,k} = \log_2\left(1 + p_{j,k}\cdot\frac{\dfrac{\left|h_{j,k}\right|^2}{N_0\cdot\dfrac{B}{K}}}{\Gamma}\right) = \log_2\left(1 + p_{j,k}\cdot\gamma_{j,k}\right) \tag{2}$$

where $p_{j,k}$ is the power of the kth sub-carrier assigned to the jth MT; $h_{j,k}$ is the channel gain of the kth sub-carrier assigned to the jth MT; N_0 is the power spectral density of additive white Gaussian noise; B is the overall available bandwidth; and K is the total number of sub-carriers. The constant Γ is called Signal-to-Noise Ratio (SNR) gap, which indicates the difference between the theoretical limit and the SNR needed to achieve a certain data transmission rate for a practical system [6]. This constant is dependent on the target Bit Error Rate (BER) and, considering an M-level Quadrature Amplitude Modulation (QAM), its value is given by $\Gamma = -[ln\,(5.BER)]/1.5$. The channel quality is characterized by the effective Channel-to-Noise Ratio (CNR) given by $\gamma_{j,k} = \frac{|h_{j,k}|^2}{N_0 \cdot \frac{B}{K} \cdot \Gamma}$

Once the achievable transmission rate per Hertz of each sub-carrier is known following expression (2), the data transmission rate of each MT can be calculated. In the sub-carrier allocation process, we assume that each sub-carrier can only be assigned to one single MT. Assuming that a sub-carrier set K_j is assigned to the jth MT, its transmission rate is calculated as

$$R_j = \sum_{k \in \mathcal{K}_j} r_{j,k} = \sum_{k \in \mathcal{K}_j} c_{j,k} \cdot \Delta f \tag{3}$$

where $c_{j,k}$ is the channel capacity per Hertz of the kth sub-carrier assigned to the jth MT and Δf is the sub-carrier bandwidth.

The throughput (average data rate) is calculated using a low-pass Simple Exponential Smoothing (SES) filtering as indicated in (4) below [6, 7].

$$T_j[n] = (1 - f_\mathrm{t}) \cdot T_j[n-1] + f_\mathrm{t} \cdot R_j[n] \tag{4}$$

where $R_j\,[n]$ is the instantaneous data rate of the jth MT calculated by (3) and f_t is a filtering constant.

In order to perform fairness evaluations, we define two kinds of User Fairness Index (UFI): rate-based and throughput based:

$$\phi_j^{\mathrm{rate}} = R_j[n] \tag{5}$$

$$\phi_j^{\mathrm{thru}} = T_j[n-1] \tag{6}$$

which are given by (3) and (4), respectively. The rate-based UFI is used when performing rate adaptive optimization based on instantaneous data rates, while the throughput-based UFI is used when performing utility-based optimization based on average data rates.

In order to measure the fairness in the rate or throughput distribution among all MTs in the cell, a Cell Fairness Index (CFI) is calculated by (7) [36].

$$\Phi = \frac{\left(\sum_{j=1}^{M} \phi_j\right)^2}{M \cdot \sum_{j=1}^{M} \left(\phi_j\right)^2} \tag{7}$$

where M is the number of MTs in the cell and φ_j is the UFI of the jth MT given by (5) or (6), depending if rate adaptive or utility-based RRA is being considered. Notice that $1/M \leq \Phi \leq 1$. A perfect fair allocation is achieved when $\Phi = 1$, which means that the rates or throughputs allocated to all MTs are equal (all UFIs are equal). The worst allocation occurs when $\Phi = 1/M$, which means that all resources were allocated to only one MT.

It was assumed that the MTs remained stationary, hence there is no need to implement any handover scheme. All users are assumed to have an in infinite amount of data to transmit during the whole simulation run (full-buffer model).

4. RESOURCE ALLOCATION ALGORITHMS

4.1. Rate adaptive sub-carrier and power allocation based on instantaneous data rates

RRA often leads to algorithms whose implementation is very complex. In fact the allocation problem is in general not convex since the allocation variable is integer and can assume only two values: 1 when the channel is allocated to a specific user and 0 otherwise. In most cases the optimal solution can be found only evaluating all possible allocations and the complexity grows exponentially in the number of users and sub-carriers. Therefore, most of the literature has been focused on the development of sub-optimal heuristics that have a lower computational complexity but that still yield good results. Many algorithms make the problem convex by relaxing the integer constraint on the allocation variable.

Unfortunately, non-integer solutions are hardly applicable in many scenarios where a sub-carrier should be actually allocated or not to a user. In the following we will focus on the rate adaptive RRA problem outlining its most common formulations and solutions.

4.1.1. Sum Rate Maximization

The mathematical formulation of the Sum Rate Maximization (SRM) RRA problem is:

$$\max_{p_{j,k},\rho_{j,k}} \sum_{j=1}^{M} \sum_{k=1}^{K} \rho_{j,k} \cdot \log_2\left(1 + p_{j,k} \cdot \gamma_{j,k}\right) \tag{8}$$

$$s.t \sum_{j=1}^{M} \sum_{k=1}^{K} p_{j,k} \leq P_{\mathrm{total}} \tag{9}$$

$$p_{j,k} \geq 0, \quad \forall j,k \tag{10}$$

$$\rho_{j,k} = \{0,1\}, \quad \forall j,k \tag{11}$$

$$\sum_{j=1}^{M} \rho_{j,k} = 1, \quad \forall k \tag{12}$$

where M is the total number of MTs; K is the total number of sub-carriers; $p_{j,k}$ is the power and $\gamma_{j,k}$ is the CNR of the kth sub-carrier assigned to the jth MT, respectively; Γ is the SNR gap; P_{total} is the Base Station (BS) total transmit power; and $\rho_{j,k}$ is the connection indicator, whose value 0 or 1 indicates whether sub-carrier k is assigned to MT j or not. On one hand, constraints (9) and (10) state that the sub-carriers' powers must be non-negative and the sum of powers among all sub-carriers must be lower or equal to the BS total transmit power. One the other hand, constraints

(11) and (12) say that each sub-carrier must be assigned to only one user at any instant of time.

In its original formulation the problem (8) has been solved in [3] by assigning each sub-carrier to the user that maximizes its gain on it and then performing waterfilling power allocation over all sub-carriers. On one hand, such a solution maximizes the cell throughput but on the other hand is extremely unfair tending to privilege the users that are closest to the BS and neglecting all the others.

4.1.2. Max-Min Rate

The RRA allocation (8) tends to starve the users with the worse channel gains, i.e. the users that are more distant from the BS. Thus, in [4] the RRA problem has been formulated with the goal of maximizing the minimum capacity offered to each user, thus introducing fairness among the users. In general, fairness among the MTs comes at the cost of a decreased overall throughput of the cell. The Max-Min Rate (MMR) RRA problem is formulated as follows:

$$\max_{p_{j,k},\rho_{j,k}} \min_{j} \sum_{k=1}^{K} \rho_{j,k} \cdot \log_2(1 + p_{j,k} \cdot \gamma_{j,k}) \quad (13)$$

$$s.t \sum_{j=1}^{M} \sum_{k=1}^{K} p_{j,k} \le P_{\text{total}} \quad (14)$$

$$p_{j,k} \ge 0, \quad \forall j,k \quad (15)$$

$$\rho_{j,k} = \{0,1\}, \quad \forall j,k \quad (16)$$

$$\sum_{j=1}^{M} \rho_{j,k} = 1, \quad \forall k \quad (17)$$

where K is the total number of sub-carriers; $p_{j,k}$ is the power and $\gamma_{j,k}$ is the CNR of the kth sub-carrier assigned to the jth MT, respectively; Γ is the SNR gap; P_{total} is the BS total transmit power; $\rho_{j,k}$ is the connection indicator, whose value 0 or 1 indicates whether sub-carrier k is assigned to MT j or not; and M is the set of MTs. Constraints (14)-(17) are the same of the SRM problem given by (9)-(12).

Unfortunately, the problem in the formulation (13) is not convex and the authors in [4] study a heuristic that is based on: a) transmitting the same amount of power (P_{max}/K) on each channel; b) implementing an assignment strategy that iteratively assigns each sub-carrier to the user with the smallest rate.

4.1.3. Sum Rate Maximization with Proportional Rate Constraints

The solution of the MMR RRA problem (13) guarantees that all users achieve a similar data rate. However, different users may require different data rates. In this case the max-min solution is not able to comply with the different user requirements. The RRA algorithm presented in [5], which is called Sum Rate Maximization with Proportional Rate Constraints (SRM-P) in the present work, is designed to allocate radio resources proportionally to different rate constraints that reflect different levels of service. The SRM-P RRA problem is formulated as follows:

$$\max_{p_{j,k},\rho_{j,k}} \sum_{j=1}^{M} \sum_{k=1}^{K} \rho_{j,k} \cdot \log_2\left(1 + p_{j,k} \cdot \gamma_{j,k}\right) \quad (18)$$

$$\sum_{j=1}^{M} \sum_{k=1}^{K} p_{j,k} \le P_{\text{total}}, \quad (19)$$

$$p_{j,k} \ge 0, \quad \forall j,k \quad (20)$$

$$\rho_{j,k} = \{0,1\}, \quad \forall j,k \quad (21)$$

$$\sum_{j=1}^{M} \rho_{j,k} = 1, \quad \forall k \quad (22)$$

$$R_i : R_j = \lambda_i : \lambda_j, \forall i,j \in \mathcal{M}, i \ne j. \quad (23)$$

where K is the total number of sub-carriers; $p_{j,k}$ is the power and $\gamma_{j,k}$ is the CNR of the kth sub-carrier assigned to the jth MT, respectively; Γ is the SNR gap; P_{total} is the BS total transmit power; $\rho_{j,k}$ is the connection indicator, whose value 0 or 1 indicates whether sub-carrier k is assigned to MT j or not; λ_j is the proportional rate requirement of the jth MT; and M is the set of MTs. Constraints (19)-(22) are the same of the SRM and MMR problems. Constraint (23) states that the user rates must follow the proportional rate requirements.

The optimization in (18) is a mixed binary integer programming problem and as such is in general very hard to solve. Thus, also in this case the problem is solved using a suboptimal heuristic and the optimization (18) is performed in two steps. In the first step, following the approach taken in [4], the sub-carriers are allocated trying to comply as much as possible with the proportional rate constraints and assuming a uniform power distribution. In the second step, having fixed the sub-carrier allocation, the power is distributed to the users so that the proportional rate constraints are met exactly.

Notice that the SRM-P problem is a combination of the SRM and MMR problems, because it combines the rate maximization of the objective function (18) with the proportional rate constraints given by (23). In the particular case where the proportional rate requirements are all equal to one, we have that the sub-carrier assignment algorithm is the same of the MMR problem described in [4]. In this way, the SRM-P RRA algorithm can achieve a kind of trade-off between resource efficiency (rate maximization) and user fairness (proportional rate requirements).

4.2. Packet Scheduling Based on Utility Theory and Average Data Rates

In this section we formulate PSC algorithms that use Utility Theory in order to find an efficient trade-off between resource efficiency and fairness among the users. The considered optimization problem is the maximization of the total utility with respect to the throughput (average data rate), which is calculated using a low-pass SES filtering as indicated in (4).

$$\max_{p_{j,k},\mathcal{K}_j} \sum_{j=1}^{M} U_j\left(T_j[n]\right) \quad (24)$$

$$s.t \sum_{j=1}^{M}\sum_{k=1}^{K} p_{j,k} \leq P_{\text{total}} \quad (25)$$

$$p_{j,k} \geq 0, \quad \forall j,k \quad (26)$$

$$\bigcup_{j\in\mathcal{M}} \mathcal{K}_j \subseteq \mathcal{K}, \quad (27)$$

$$\mathcal{K}_i \bigcap \mathcal{K}_j = \emptyset, \forall i,j \in \mathcal{M}, i \neq j. \quad (28)$$

where K_j is the subset of sub-carriers assigned to the jth MT, K is the set of all sub-carriers in the system, M is the set of all MTs in the system, $p_{j,k}$ is the power of the kth sub-carrier assigned to the jth MT, P_{total} is total transmit power of the cell, and $U_j\ (T_j\ [n])$ is a concave and increasing utility function based on the current throughput $T_j\ [n]$ of the jth MT. On one hand, constraints (25) and (26) state that the sub-carriers' powers must be non-negative and the sum of powers among all sub-carriers must be lower or equal to the BS total transmit power. One the other hand, constraints (27) and (28) say that there is a limited number of sub-carriers and that each one of them must be assigned to only one user at any instant of time.

The optimum solution for the joint optimization problem (24)-(28) is still an open problem. The majority of the sub-optimum solutions proposed in the literature are based on the problem-splitting technique, which splits problem (24)-(28) in two stages: DSA and APA. In the present work, we also use this technique, as explained in the following.

Evaluating the objective function in (24) and the throughput expression in (4), the derivative of $U_j(T_j)$ with respect to the transmission rate R_j is given by:

$$\frac{\partial U_j}{\partial R_j} = \frac{\partial U_j}{\partial T_j}\cdot\frac{\partial T_j}{\partial R_j} = f_{\mathrm{t}}\cdot\frac{\partial U_j}{\partial T_j}|_{T_j=(1-f_{\mathrm{t}})T_j[n-1]+f_{\mathrm{t}}R_j[n]}$$

where f_t is the filtering constant in the throughput calculation. In the case that f_t is sufficiently small, the expression above can be further simplified, as indicated below [7].

$$\frac{\partial U_j\left(T_j[n]\right)}{\partial R_j[n]} \approx f_{\mathrm{t}}\cdot\frac{\partial U_j}{\partial T_j}|_{T_j=T_j[n-1]}$$

where the previous resource allocation totally determines the current values of the marginal utilities. Using the one-order Taylor formula, the following expression can be derived [7]:

$$\sum_{j\in\mathcal{M}} U_j\left(T_j[n]\right) - \sum_{j\in\mathcal{M}} U_j\left(T_j[n-1]\right) \approx$$
$$\sum_{j\in\mathcal{M}} \frac{\partial U_j}{\partial T_j}|_{T_j=T_j[n-1]}\cdot\left(f_{\mathrm{t}}\cdot R_j[n] - f_{\mathrm{t}}\cdot T_j[n-1]\right)$$

The maximization of the expression above leads to the maximization of (24). Since f_t is a constant and $T_j[n-1]$ is fixed at the current TTI n, the objective function of our simplified optimization problem becomes linear, as can be seen in the following.

$$\max_{p_{j,k},\mathcal{K}_j} \sum_{j\in\mathcal{M}} U_j'\left(T_j[n-1]\right)\cdot R_j[n] \quad (29)$$

where $U_j'\ (T_j[n-1]) = \frac{\partial U_j}{\partial T_j}\Big|T_j = T_j[n-1]$ is the marginal utility of the jth MT with respect to his throughput in the previous TTI. The optimization problem (29) is a weighted sum rate maximization problem [37], whose weights are adaptively controlled by the marginal utilities. The mathematical development presented above shows that the instantaneous optimization maximizing (29) leads to a long-term optimization that maximizes (24).

The linear objective function greatly simplifies the corresponding algorithms. The DSA problem, which is the optimization problem (24)-(28) with equal power allocation, has a closed form solution [7, 38]. The MT j^* is chosen to transmit on the kth sub-carrier in the nth TTI if it satisfies the condition given by (30):

$$j^* = \arg\max_j\left\{U_j{}'\left(T_j[n-1]\right)\cdot c_{j,k}[n]\right\}, \quad \forall j \quad (30)$$

where $U_j'(.)$ is the marginal utility of the jth MT, $T_j[n-1]$ is the throughput of the jth MT up to TTI $n-1$, and $c_{j,k}\ [n]$ denotes the instantaneous achievable transmission efficiency of the jth MT on the kth sub-carrier.

In this paper we will consider a family of utility functions of the form presented in (31) below [32].

$$U_j\left(T_j[n]\right) = \frac{T_j[n]^{1-\alpha}}{1-\alpha} \quad (31)$$

where α is a non-negative parameter that determines the degree of fairness. The fairness of the utility function becomes stricter as α increases. In the present work we call the RRA policy derived from the use of this particular utility function as utility-based alpha-rule, which is a generalization of the original alpha-rule proposed in [24].

According to (30), this is equivalent to consider a priority function of the PSC algorithm given by:

$$P_{j,k}^{PSC} = \frac{c_{j,k}[n]}{T_j[n-1]^{\alpha}}, \quad \forall j,k; \quad \alpha\in[0,\infty) \quad (32)$$

For each of the K sub-carriers in the system, a multi-carrier PSC algorithm calculates the priority functions for all J MTs according to (32) and assign it to the MT that has the highest priority value.

We will show in sections 4.2.1, 4.2.2 and 4.2.3 that, depending on the value of the parameter α, the general utility framework presented above can be designed to work as any of three well-known classical PSC algorithms: Max-Rate (MR), Max-Min Fairness (MMF) and Proportional Fairness (PF). Furthermore, in section 4.2.4 we present the Adaptive Throughput-Based Fairness (ATF) PSC algorithm, which can achieve an adaptive trade-off between resource efficiency and fairness according to the cellular operator's objectives.

4.2.1. Max-Rate

The MR PSC algorithm is able to maximize the system spectral efficiency because it considers a linear utility function $U_j\left(T_j[n]\right) = T_j[n]$, which yields a constant marginal utility $U_j^{\prime}\left(T_j[n]\right) = 1$ [6, 7]. One can notice that this can be achieved setting α=0 in (31). According to (32), this is equivalent to consider a priority function related to the MR algorithm given by (33) below.

$$P_{j,k}^{\mathrm{MR}} = c_{j,k}[n], \quad \forall j, k \tag{33}$$

As the final result, each sub-carrier will be assigned to the MT that has the highest channel gain on it. The MR criterion maximizes the system capacity at the cost of unfairness among the MTs, because those with poor radio link quality probably will not have chance to transmit.

4.2.2. Max-Min Fairness

The utility function of the MMF algorithm is the limit of the function in (31), when $\alpha \to \infty$ [30].

According to (30) and (32), the priority function is dependent on the marginal utility $U_j^{\prime}\left(T_j[n]\right)$ and the achievable instantaneous transmission efficiency $c_{j,k}[n]$. However, in the case of the MMF criteria and when considering MTs with lower data rates, the influence of the marginal utility when $\alpha \to \infty$ is so high that the influence of the channel quality becomes negligible. Taking this fact into account, we can assume a more simplified priority function for the MMF algorithm given in (34), which is also known in the literature as the "Fair Throughput" criterion [39].

$$P_{j,k}^{\mathrm{MMF}} = \frac{1}{T_j[n-1]}, \quad \forall j, k \tag{34}$$

which gives priority to the MT that has experienced the worst throughput so far. In this way, in terms of throughput distribution, it is the fairest criterion possible, since all MTs will have approximately the same throughput in the long-term. However, since this criterion maximizes the throughput of the worst MTs, it will provide low aggregate system throughput.

4.2.3. Proportional Fairness

A trade-off between resource efficiency and fairness can be achieved by means of the PF PSC algorithm [26]. In utility theory, the logarithmic utility function is associated with the proportional fairness [6, 7]. In the general family of utility functions presented in (31), the logarithmic function can be achieved when $\alpha \to 1$ (see proof on [30]). Therefore, according to (32), the priority function of the PF algorithm is given by (35).

$$P_{j,k}^{\mathrm{PF}} = \frac{c_{j,k}[n]}{T_j[n-1]}, \quad \forall j, k \tag{35}$$

4.2.4. Adaptive Throughput-Based Fairness

The ATF PSC algorithm, which was proposed in [40], joins in a unified framework the three aforementioned classical PSC algorithms (MR, MMF and PF). In the light of utility theory, it was shown that a general PSC algorithm based on (31) is able to provide several degrees of fairness. The ATF algorithm adaptively explores this flexibility in order to achieve an efficient trade-off between resource efficiency and fairness planned by the network operator. However, it is difficult to design an adaptive control of the α parameter because it is defined over a large range of values. Instead of that, the ATF algorithm transforms the priority function of (32) into another priority function that is based on a parameter β, which is defined over a controlled range and provides the possibility of a stable and simple adaptive control. The priority function of the ATF algorithm is presented in (36) below.

$$P_{j,k}^{\mathrm{ATF}} = \frac{c_{j,k}[n]^{1-\beta}}{T_j[n-1]^{\beta}}, \quad \forall j, k; \quad \beta \in [0,1] \tag{36}$$

Notice that in a conceptual point of view, the priority functions on (32) and (36) perform in the same way. The ATF algorithm is able to work as the classical PSC algorithms by means of the adaptation of the β parameter. The values of $\beta = \{0, 0.5, 1\}$ corresponds to the MR, PF and MMF, respectively.

The ATF algorithm uses the User Fairness Index (UFI) Φ_j^{thru} and the Cell Fairness Index (CFI) Φ, which are given by (6) and (7), respectively.

The objective of the ATF algorithm is to assure a strict fairness distribution among the MTs, i.e. the CFI Φ must be kept around a planned value Φ_{target}. Therefore, the ATF algorithm adapts the parameter β in the scheduling policy presented in (36) in order to achieve the desired operation point. In order to do that, the new value of the parameter β is calculated using a feedback control loop of the form:

$$\beta[n] = \beta[n-1] - \eta \cdot \left(\Phi_{\mathrm{filt}}[n] - \Phi_{\mathrm{target}}\right) \tag{37}$$

where $\Phi_{filt}[n]$ is a filtered version of the CFI using a SES filtering, Φ_{target} target is the desired value for the index, and the parameter η is a step size that controls the adaptation speed of the parameter β. Notice that a SES filter, which is suitable for time series with slowly varying trends, was used to suppresses short-run fluctuations and smooth the time series $\Phi[n]$.

5. SIMULATION RESULTS

In this section the simulation parameters as well as the simulation results are presented. The main simulation parameters are presented in Table 1.

The metrics used for evaluation and comparison of the investigated resource allocation algorithms were:

- Total cell throughput (resource allocation efficiency factor);

- Cell fairness index (according to (7)). It was assumed that the user fairness index Φ_j used in (7) was Φ_j^{rate} given by (5) for the case of rate adaptive RRA algorithms based on instantaneous data rate, or Φ_j^{thru} given by (6) for the case of utility-based PSC algorithm based on average data rate (throughput);
- User satisfaction (percentage of satisfied users in the cell). A user is considered satisfied if the achieved throughput at the end of his session is equal or higher than a threshold, which is indicated in Table 1;
- Mean user throughput as a way to analyze the opportunism in the resource allocation.

Table 1. Parameters used in the simulations

Parameter	Value
Number of cells	1
BS transmission power	1 W
Cell radius	500 m
MT speed	static
Carrier frequency	2 GHz
Number of sub-carriers	192
Sub-carrier bandwidth	15 kHz
Path loss	using (1)
Log-normal shadowing standard dev.	8 dB
Small-scale fading	Typical Urban
AWGN power per sub-carrier	-123.24 dBm
BER requirement	10^{-6}
Link adaptation	using (2)
TTI	0.5 ms
Traffic model	Full buffer
Throughput filtering constant (f_t)	0.02
Minimum β value	0
Maximum β value	1
ATF PSC control time window	0.5
ATF PSC target fairness index (Φ_{target})	0.5 or 0.9
ATF PSC step size (η)	0.1
ATF PSC filtering constant	0.1
Throughput requirement	640 kbps

The results presented in this section are obtained for all rate adaptive RRA algorithms presented in section 4.1 averaged over 100 snapshots (each with a simulation time span of 0.5s), and all utility-based PSC algorithms described in section 4.2 averaged over 10 snapshots (each with a simulation time span of 30s). The difference in the duration of the simulations is due to the fact that the utility-based optimization is based on average data rates and so it requires a larger time window. For the rate adaptive SRM-P algorithm (see section 4.1.3), the proportional rate requirements are set equal to one for all users, i.e. $\lambda_j = 1\ (j = 1, \ldots, M)$. In the case of the utility-based packet scheduling analysis, the power distribution over all sub-carriers was uniform with no power adaptation.

Fig. 2 shows the mean cell fairness index calculated using (7) for different cell loads and various RRA algorithms. In this case the rate adaptive MMR and utility-based MMF algorithms outperform all the others. As expected, the SRM resource allocation and the MR PSC algorithms, which are designed to use the resources in the most efficient way, are the ones that present the lowest fairness indexes. The SRM-P resource allocation and the PF PSC algorithms achieve a static trade-off between resource efficiency and user fairness. The latter presents a more visible trade-off since the former shows a performance very close to the MMR resource allocation algorithm. Regarding the ATF PSC algorithm, we run simulations with two different target CFIs: 0.5 and 0.9. It can be observed that ATF is successful to achieve its main objective, which is to guarantee a strict fairness distribution among the MTs. This is achieved due to the feedback control loop that dynamically adapts the parameter β of the ATF priority function (see (36)). The advantage of the ATF algorithm in comparison with the others is that it can be designed to provide any required fairness distribution, while the other strategies are static and do not have the freedom to adapt themselves and guarantee a specific performance result.

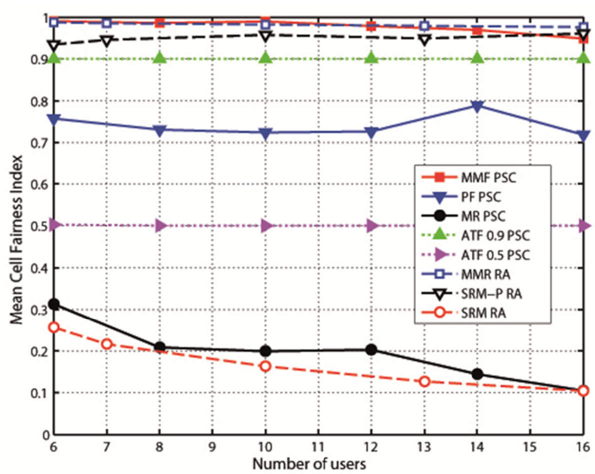

Fig. 2. Cell fairness index as a function of the number of users.

Fig. 3 shows the total cell throughput for the different algorithms. As expected, the SRM resource allocation and the MR PSC algorithms are able to maximize the resource efficiency, while MMR and MMF present the lowest cell throughput. Since SRM-P and PF are trade-offs between SRM/MR and MMR/MMF, their performance lied between those extremes. Looking at Fig. 2, one can expect that depending on the value of the ATF target fairness index, the ATF resource efficiency would be somewhere in the middle between the performances of MMF, PF and MR. This can be observed in Fig. 3. On one hand, when the ATF target fairness index is set to 0.5, ATF works as an hybrid scheduling policy between PF and MR. On the other hand, the ATF performance in terms of total cell throughput lies between MMF and PF when the target fairness index is set to 0.9. Notice that the throughput values presented by the MR PSC algorithm are lower than those observed with the rate adaptive SRM resource allocation. This was due to the fact that the simulations carried out for the PSC investigation did not consider power adaptation.

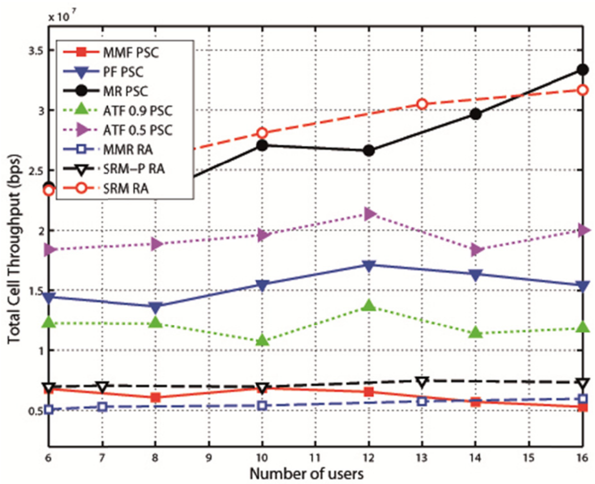

Fig. 3. Total cell throughput as a function of the number of users.

The user satisfaction as a function of the number of users is depicted in Fig. 4. It is interesting to see that the algorithms that achieve a trade-off between resource efficiency and user fairness, namely SRM-P, PF and ATF, are the ones that present the highest user satisfaction. This indicates that it is not advantageous in terms of user satisfaction to use RRA algorithms that are located in the extremes of the efficiency-fairness plane (maximization of system capacity or maximization of user fairness). In general terms, the algorithms that maximize capacity achieve low and almost constant user satisfaction because they always give priority to few users with best channel conditions. On the other hand, the algorithms that privilege user fairness present higher satisfaction for low system load but the performance decreases very fast when the number of users increases. Regarding the algorithms able to achieve a trade-off, the utility-based PSC algorithms (PF and ATF) are preferable than the rate adaptive SRM-P resource allocation, since they present higher user satisfaction for all the range of system loads considered in this study.

It can be concluded from Figs. 2, 3 and 4 that the adaptive ATF PSC algorithm is the most flexible technique able to control the trade-off between resource efficiency and user fairness while maintaining good satisfaction levels for the users. In order to have a deeper insight into the functioning of the ATF PSC algorithm, Fig. 5 is presented. This figure analyzes the opportunistic resource allocation of the ATF policy depicting the mean user throughput as a function of the number of users with several CFIs. The users are divided into two groups of equal size: inner and outer. The former is composed by the users with best channel conditions considering path loss and shadowing (close to the BS), while the latter is composed by the users with worst channel conditions (far from the BS).

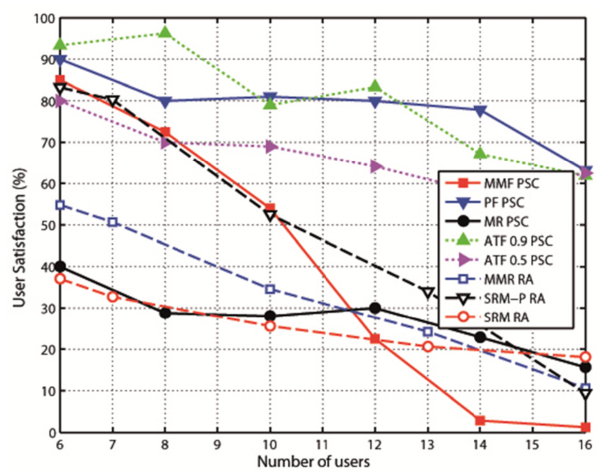

Fig. 4. User satisfaction as a function of the number of users.

Observing Fig. 5, one can notice that the closer the performance of the inner and outer groups, the fairer the resource allocation of the ATF algorithm (higher CFIs). The opposite is also true: when the ATF algorithm is configured with a low CFI, the performance of the user groups diverge, indicating that the inner group is privileged in detriment of the outer group. Furthermore, trying to approximate the performance of the user groups by using a fairer RRA policy has the disadvantage of decreasing the mean throughput of the users of both groups, which leads to the decrease of the total cell throughput (see Fig. 3) and also the decrease of user satisfaction when the system is loaded (see Fig. 4). Unfair RRA policies give priority to the inner group. Since they have good channel conditions, the efficiency in the resource usage will be high, as can be seen in Fig. 3, and the satisfaction of these users will always be guaranteed no matter how loaded the system is, as can be observed in Fig. 4.

One last issue that should be taken into account is complexity. In general, the rate adaptive RRA strategies considered in this work, which are comprised of DSA and APA algorithms and are based on instantaneous data rate, present higher computational complexity than their counterparts that use utility-based PSC algorithms and are based on average data rates. Using less computational resources, the utility-based PSC algorithms show approximately the same performance in terms of fairness and system capacity and better performance in terms of user satisfaction than the rate adaptive RRA algorithms.

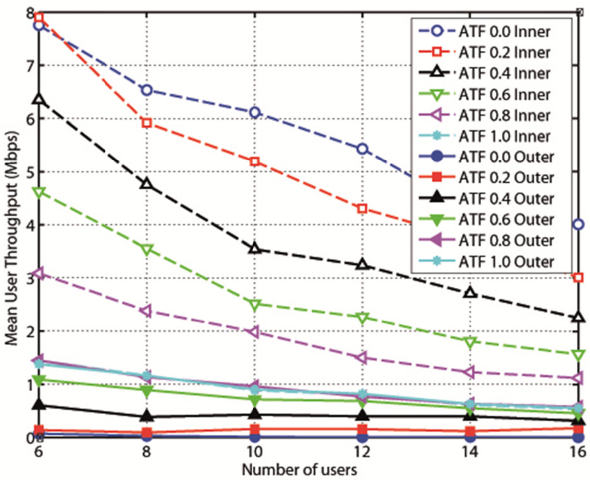

Fig. 5. Mean user throughput as a function of the number of users for the ATF policy considering inner and outer groups.

6. CONCLUSIONS

In this paper we investigated the trade-off between resource efficiency and fairness among users in OFDMA-based cellular networks. Two RRM approaches were studied: rate adaptive resource allocation (sub-carriers and power) based on instantaneous data rate and utility-based packet scheduling based on average data rate (throughput). Comparing the two approaches, one can see clearly the direct relationship between SRM RRA and MR PSC, and also MMR RRA and MMF PSC. Furthermore, possible trade-offs were presented, such as SRM-P in the case of rate adaptive RRA, and PF and ATF in the case of utility-based PSC.

It was concluded from the simulation results in a single-cell scenario that it is possible to achieve an efficient trade-off between resource efficiency and fairness using any of the two RRM approaches. However, utility-based PSC algorithms have the advantage of presenting higher user satisfaction with less computational complexity.

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