Enhanced Base Station Assignment Approach for Coping with Backhaul Constraints in OFDMA-based Cellular Networks

Hiram Galeana, Ramon Ferrús
Dept. Signal Theory and Communications (TSC)
Universitat Politècnica de Catalunya (UPC)
Barcelona, Spain
{hiram.galeana,ferrus}@tsc.upc.edu

Abstract—**In this paper we extend the base station (BS) assignment problem to incorporate backhaul related constraints into the assignment decision. This is motivated by the fact that the deployment of more spectral efficient radio access technologies are currently imposing stringent bandwidth requirements at cell sites, and there is a growing concern that backhaul network can become a new network bottleneck in certain deployment scenarios. Unlike existing assignment approaches, we propose a BS assignment algorithm envisioned as a suitable technique capable to cope, at some extent, with possible backhaul congestion situations in OFDMA-based systems. Simulation results demonstrate that the proposed algorithm can provide the same system capacity with less backhaul resources so that, under backhaul bottleneck situations, a better overall network performance is effectively achieved.**

Keywords- backhaul; base station assignment; OFDMA.

I. Introduction

Next generation mobile broadband solutions have clearly consolidated the adoption of orthogonal frequency division multiple access (OFDMA) schemes as an efficient technology for wireless transmission, both in the public cellular arena (e.g., 3GPP LTE and Mobile WiMAX networks) as well as in the path towards supporting broadband data rates in other specialised wireless communications solutions (e.g., advanced PMR systems). OFDMA splits the entire bandwidth into several sets of subcarriers and allows for the exploitation of multiuser diversity by managing both time and frequency components in the radio resource allocation process [1]. To fully exploit OFDMA capabilities, efficient radio resource allocation techniques are crucial. In this context, the BS assignment problem, that is, the selection of the most appropriate BS to handle radio transmission to/from mobile terminals, constitutes a key component of the overall resource allocation process [2]. So far, existing BS assignment solutions (e.g., [2]-[5]) consider that the main bottleneck of wireless systems is on the air interface. This assumption has been proven to be valid for traditional cellular voice networks where, as the aggregate traffic rate supported per cell site is relatively low, backhaul dimensioning accounting for air interface peak rates was an economically feasible option. However, as OFDMA-based systems are able to deliver high peak data rates over the air interface, a dimensioning approach of the mobile backhaul network based on peak rate capacities no longer constitutes an efficient option. It's worth noting that mechanisms like Adaptive Modulation and Coding (AMC) and soft frequency reuse techniques used in OFDMA networks can turn into a high variation between the mean and peak aggregate traffic rate supported in a given BS attending to the users' spatial distribution (e.g., if users are close to the BS, the aggregated rate supported in the air interface can be several times higher than that achieved under an uniform user distribution).

Hence, considering that backhaul costs could represent as much as one quarter of the total of network costs [6], operators may be hesitant to invest from the beginning in additional backhaul capacity to support temporary peak data rates during busy hours, so it becomes essential to make an efficient use of the available transmission resources. At this regard, best practices for backhaul design has been recently issued by NGMN Alliance [7] and there is an increasing number of solutions that can be adopted from different vendors to optimize the backhaul network [8]. As well, flow control mechanisms have been introduced in current mobile networks between BSs and radio controllers to partially mitigate traffic peaks in the backhaul links at the expenses of an increased delay in some services [9], [10]. Attending to previous considerations, the probability of facing a situation where the backhaul capacity of a given cell site becomes the bottleneck should not be underestimated [11].

In this paper we propose to take into consideration the available backhaul capacity into the radio resource allocation process of an OFDMA network, and, in particular, within the BS assignment process. We develop a backhaul-aware BS assignment algorithm envisioned as a suitable technique capable to cope, at some extent, with possible backhaul congestion situations in OFDMA-based systems. The basic idea behind the proposed BS assignment algorithm is to prevent the assignment of users to their "best radio" BSs when backhaul congestion arises by means of redirecting them to neighboring BSs with enough radio and backhaul capacity. It is clear that this possibility comes at the expenses of a less efficient utilization of radio resources as some users are going to be served by BSs other than their "best radio" BS. However, this unavoidable tradeoff between reducing congestion in backhaul and an efficient usage of the radio is proven to be successfully exploited by the proposed algorithm, turning

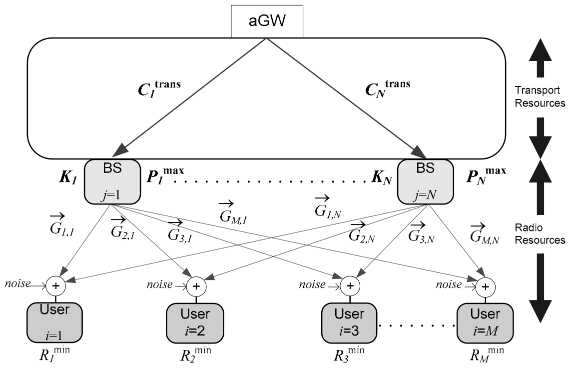


Figure 1. Model of an OFDMA-based system. The arrows between each user and BSs indicate possible connection choices.

ultimately into a better overall system performance. The remainder of the paper is organized as follows. Next section describes the system model of an OFDMA-based network. The formulation of the BS assignment problem that includes backhaul constraints is introduced in section III. The mapping of the problem to an MMKP and the description of proposed algorithm to solve the problem are given in section IV. Section V provides numerical results regarding the performance of the BS assignment algorithm and concluding remarks of the paper are presented in section VI.

II. System Model

We consider a downlink OFDMA-based cellular network with N BSs that cover a geographical area in which there are M active users, as illustrated in Fig. 1. Each user $i\in\{1,\ldots,M\}$ is assumed to have a minimum data rate requirement, denoted as $R_i^{\min}$. The overall network uses a single frequency channel with a total bandwidth BW that it is divided into K OFDM subcarriers so that each BS $j\in\{1,\ldots,N\}$, can operate a subset of K_j subcarriers attending to a given reuse pattern. Radio and transport resources are assumed to be allocated to each user in a single BS, i.e., no macrodiversity support is considered. The model considers that each BS is constrained by a limited amount of radio and transport resources. As to radio resource constraints, each BS is assumed to be able to allocate simultaneously a maximum of K_j subcarriers and has a maximum downlink transmission power limitation $P_j^{\max}$. The radio channel gain between BS j and user i is modeled by a vector $\vec{G}_{i,j} = G_{i,j,1},\ldots G_{i,j,k}$ where $G_{i,j,k}$ denotes the radio channel gain over subcarrier $k\in\{1,\ldots,K_j\}$. As to transport resource constraints, we assumed that each BS j is provisioned with a maximum transport capacity C_j^{trans} (in bits/sec), i.e., the available bandwidth in the path connecting BS j with an upper node, called here as the access gateway (aGW), in the mobile network.

For each possible assignment, we need to first determine the amount of resources required by each user to fulfil users' rate requirements. This is done by defining a radio cost function, denoted as α_{ij}, and a transport cost function, indicated as β_{ij}, to reflect the resource consumption when assigning user i to BS j. In addition, a utility function is also defined in order to quantify the appropriateness of each BS assignment in terms of the bit rate efficiency of the allocated resources. Details of utility and resource cost functions are provided in the following.

A. Radio Resource Cost

In a cellular OFDMA system, the computation of the SINR achieved at subcarrier k in the receiver of user i served by BS j, is obtained as follows:

$$SINR_{i,j,k} = \frac{G_{i,j,k}P_{i,j,k}}{I_{i,j,k}+\eta} \tag{1}$$

where $G_{i,j,k}$ is the radio channel gain between BS j and user i over subcarrier k, $P_{i,j,k}$ is the transmit power of BS j on subcarrier k allocated to user i, η is the thermal noise per subcarrier, and $I_{i,j,k}$ is the co-channel interference (CCI) power received by user i in that subcarrier. The value of the co-channel interference $I_{i,j,k}$ can be computed as:

$$I_{i,j,k} = \sum_{n=1,n\neq j}^{n=N} G_{i,n,k}P_{m\neq i,n,k}$$

where $P_{i,n,k}$ is the transmit power of interfering BS n, on subcarrier k assigned to other user $m \neq i$. Equation (1) denotes the channel frequency response of user i on subcarrier k, and the achievable transmission rate $r_{i,j,k}$ on this subcarrier of user i assigned to BS j is given by:

$$r_{i,j,k} = \frac{BW}{K}\cdot\log_2\left(1+SINR_{i,j,k}\right) \tag{2}$$

Hence, if all the resources of BS j were allocated to user i, the maximum achievable rate would be:

$$R_{i,j}^{\max} = \sum_{k=1}^{K_j} r_{i,j,k} \tag{3}$$

Over such a basis, considering that BS j allocates a given amount of subcarriers to user i, denoted as K_{ij}, being $K_{ij} < K_j$, during the transmission time ΔT_{ij}, being $\Delta T_{ij} < T_s$, where T_s is a scheduling reference time, we could relate the achievable rate to the amount of used subcarriers and the amount of allocated transmission time, required to meet user's minimum rate requirement:

$$\frac{K_{ij}}{K_j}\frac{\Delta T_{ij}}{T_s}R_{ij}^{\max} \geq R_i^{\min}$$

From previous expression, the radio resource cost α_{ij} is defined directly as:

$$\alpha_{ij} \triangleq \frac{R_i^{\min}}{R_{ij}^{\max}} = \frac{K_{ij}}{K_j}\frac{\Delta T_{ij}}{T_s} \leq 1 \tag{4}$$

where α_{ij}=1 would mean that user i makes use of all available radio resources at BS j. Attending to practical considerations, it is considered that there is a limited set of modulation and coding schemes (MCS) that must be used on each subcarrier, thus reducing the output of (2)-(4) to a set of discrete values. Thus, we can define the peak rate over the air interface of BS j, denoted as C_j^{air}, as the highest achievable aggregate data rate when using all subcarriers continuously with the highest rate MCS.

B. Transport Resource Cost

The transport cost β_{ij} associated with the assignment of user i to BS j is defined as the ratio of the required user bit rate $R_i^{\min}$ to the available transport capacity of BS j, denoted as C_j^{trans}, that is:

$$\beta_{ij} \triangleq \frac{R_i^{\min}}{C_j^{trans}} \tag{5}$$

As a matter of clearly relating the transport capacity C_j^{trans}, to the peak rate of the radio interface C_j^{air}, we define the transport capacity factor ϕ_j as follows:

$$\phi_j \triangleq \frac{C_j^{trans}}{C_j^{air}} \tag{6}$$

Note that ϕ_j=1 would indicate that the transport capacity of BS j has been provisioned to support the maximum throughput that the air interface can achieve.

C. Utility Function

Commonly, a utility function is a non-decreasing function of the amount of allocated network resources and its shape (e.g., step, convex, concave or sigmoid are often used) depends on the expected benefit that resource allocation can bring into a given system [12]. We formulate the utility function to reflect the bit rate efficiency of the allocated resources to supporting the data transfer of each user assigned to a given BS. The utility function u_{ij} denotes the suitability of each assignment, so $u_{ij} > u_{il}$ would mean that BS l is more appropriate than BS l to serve user i in terms of the bit rate efficiency. As well, $u_{ij} > u_{lj}$ would indicate that is better to assign user i to BS j than user l. Over such a basis, the air interface efficiency is directly computed as the spectral efficiency. As to the transport resources, it's assumed that all assignments have the same efficiency. That is, the resources needed to transport 1b/s of a user between the aGW and the correspondent BS are assumed to be the same for all BSs, noticing here that other assumptions, e.g., based on transport provisioning costs, could be also possible but are out of the scope of this work. Hence, the utility function is defined as:

$$u_{ij} = \sum_{k=1}^{K_j} \log_2(1 + SINR_{i,j,k}) \tag{7}$$

Then, assignments to BSs where users have high values of SINR are favored.

III. Problem Formulation

The BS assignment problem is modelled as a non-linear optimization problem aimed to find an assignment solution for which a maximum utility is attained subject to a set of radio (BS power) and backhaul (aggregate bit rate) resource constraints and also attending to minimum user bit rate requirements. Let $B = \{b_{ij}\}_{MxN}$ denote the BS assignment matrix, where variable b_{ij}=1 if user i is assigned to BS j, or zero otherwise. The BS assignment problem can be formally written as:

$$\max_{ij}\left(\sum_{i=1}^{M}\sum_{j=1}^{N} u_{ij} b_{ij}\right) \tag{8}$$

$$\sum_{i=1}^{M} \alpha_{ij} b_{ij} \le 1 \qquad j = 1,...,N \tag{9}$$

$$\sum_{i=1}^{M} \beta_{ij} b_{ij} \le 1 \qquad j = 1,...,N \tag{10}$$

$$\sum_{j=1}^{N} b_{ij} = 1 \qquad i = 1,...,M \tag{11}$$

$$R_i \ge R_i^{\min} \tag{12}$$

$$b_{ij} \in \{0,1\} \tag{13}$$

The optimization problem aims to maximize the total welfare utility (8) of the assignments in the system. Under the considered objective function, the assignments that lead to have a most efficient connection, in terms of the bit rate efficiency of the allocated radio resources, are preferred. The set of constraints in (9) and (10) assures that no more resources than available are assigned to each BS. The third set of constraints (11) denotes that all users need to be assigned to a single BS, while (12) indicates the individual rate required by each user. Moreover, to avoid splitting or partial assignment of users, constraint (13) is used, which however leads to the combinatorial nature of the problem with exponentially growing complexity in the degrees of freedom.

Problem (8)-(13) is a non-linear combinatorial optimization problem since entries in the assignment matrix B can only take integer values. Notice that utility and radio resource cost functions are non-linear functions that depend on the SINR values, which in turn depend on the BS assignment of users because of the CCI. This means that utility and radio resource cost function values are coupled with the assignment of the users in the system, which brings more complexity into the BS assignment problem. To overcome this issue, we re-formulate the BS assignment problem under the practical consideration of considering a fully-loaded system [2], where BSs are assumed to transmit at maximum power. In addition, we consider that the maximum transmission power of BS j is distributed uniformly, on average, over the K_j subcarriers. Then, the co-channel interference can be re-written as:

$$I_{i,j,k} = \sum_{n=1,n\ne j}^{n=N} G_{i,n,k} P_{m\ne i,n,k} \le I_{i,j,k}^{\max} = \sum_{n=1,n\ne j}^{n=N_k} G_{i,n,k} \frac{P_n^{\max}}{K_n} \tag{14}$$

where $I_{i,j,k}$ is the maximum co-channel interference value that user i can observe under full load conditions, and $P_n^{\max}$ is the maximum power limit of the interfering BS n. In this way, the computation of SINR under full load conditions by means of (1) does not depend on the BS assignment, neither do utility and radio costs values. The BS assignment problem in (8)-(13) can be mapped into a Multiple-Choice Multidimensional Knapsack Problem (MMKP) [13]. A MMKP considers a set of items, classified in I disjoint groups of J_i items each, and a knapsack to pack some of them whose available capacity is modelled by means of S distinct resource constraints represented by (W_1, W_2,…, W_S). Packing item j from group i in the knapsack provides a utility given by u_{ij} at the expenses of requiring a portion of the knapsack capacity given by

W_{ij}={$(w_{ij})^1/W_1$, $(w_{ij})^2/W_2$,…, $(w_{ij})^S/W_S$}. The objective of the MMKP is to exactly select one item from each group to achieve the maximum aggregated utility without exceeding knapsack's capacity.

The MMKP problem is equivalent to our original optimization problem given by (8)-(13) attending the following considerations. The number of groups I is given by the number of users M. The set of items J_i within the group i are the set of N BSs where the user can be allocated. The number of limiting resources is S=2N since there are N BSs and each BS has two resource constraints. The vector representing the amount of resources required for serving user i in BS j (i.e., choosing item j from group i) can be arranged so that $W_{ij} = (\alpha_{ij}^1,\ldots,\alpha_{ij}^s,\ldots,\alpha_{ij}^N, \beta_{ij}^1,\ldots,\beta_{ij}^s,\ldots,\beta_{ij}^N)$, where α_{ij}^s and β_{ij}^s are described next. Considering that allocation of BS j to user i only requires resources in the serving BS j, $\alpha_{ij}^s = \alpha_{ij}$ and $\beta_{ij}^s = \beta_{ij}$ if s=j, and $\alpha_{ij}^s = 0$ and β_{ij}^s =0 otherwise, being α_{ij} and β_{ij} the resource costs modelled by (4) and (5), respectively.

IV. BS Assignment Algorithm

The proposed algorithm for solving the BS assignment problem is based on [14], which makes Lagrange multipliers applicable to discrete optimization problems such as the MMKP. It is worth clarifying that the approach described in [14] have already been considered as a useful tool in some works [15] to solve resource allocation problems in OFDMA wireless networks. The framework behind the algorithm used in this paper was introduced in our previous work for CDMA networks detailed in [16]. Over such a basis, we have adapted the algorithm to the BS assignment problem in OFDMA networks. According to [17], the optimal solution $b_{ij}^*\in\{0,1\}$ of the unconstrained maximization problem

$$\max_{ij}\left\{\left(\sum_{i=1}^{M}\sum_{j=1}^{N}u_{ij}b_{ij}\right)-\sum_{j=1}^{N}\lambda_j\sum_{i=1}^{M}\alpha_{ij}b_{ij}-\sum_{j=1}^{N}\mu_j\sum_{i=1}^{M}\beta_{ij}b_{ij}\right\} \quad (15)$$

where λ_j and μ_j with $j\in\{1,\ldots,N\}$, are non-negative Lagrange multipliers associated to radio and transport constraints of each BS, respectively, is also the optimal solution for the constrained optimization problem:

$$\max_{ij}\left(\sum_{i=1}^{M}\sum_{j=1}^{N}u_{ij}b_{ij}\right) \quad (16)$$

$$\sum_{i=1}^{M}\alpha_{ij}b_{ij}\le\sum_{i=1}^{M}\alpha_{ij}b_{ij}^*\triangleq\pi_j \qquad j=1,\ldots,N \quad (17)$$

$$\sum_{i=1}^{M}\beta_{ij}b_{ij}\le\sum_{i=1}^{M}\beta_{ij}b_{ij}^*\triangleq\tau_j \qquad j=1,\ldots,N \quad (18)$$

that is equivalent to our BS assignment problem except for condition (11) discussed later on. From (15) it is noted that, if Lagrange multipliers λ_j and μ_j are known, the optimization problem can be easily solved. In fact, rewritten (15) as:

$$\max_{ij}\left\{\sum_{i=1}^{M}\sum_{j=1}^{N}(u_{ij}-\lambda_j\alpha_{ij}-\mu_j\beta_{ij})b_{ij}\right\}$$

the optimal solution is given by:

$$b_{ij}^*=\begin{cases}1 & \text{if} \quad w_{ij}=u_{ij}-\lambda_j\alpha_{ij}-\mu_j\beta_{ij}>0\\ 0 & \text{otherwise}\end{cases} \quad (19)$$

where w_{ij} is defined as the weighted utility, a metric that integrates the utility, resource costs and Lagrange multipliers regarding to each resource constraint. The constraint (11) related to group constraints can be easily taken into account by selecting, among possible assignments choices in (19), the one that provides the maximum weighted utility. Hence, the BS assignment problem can be solved by computing the set of 2N multipliers. The solution is feasible if the amount of radio and transport resources allocated in each BS, denoted as π_j and τ_j, in (17) and (18), respectively, do not exceed available resources. Furthermore, the solution is optimal if the following condition is held:

$$\sum_{j=1}^{N}\lambda_j(1-\pi_j)+\sum_{j=1}^{N}\mu_j(1-\tau_j)=0$$

The main difficulty in solving the problem is how to efficiently compute the Lagrange multipliers. In this regard, we follow the approach used in [14] that is based upon the concept of graceful degradation of the most valuable choices. First, an initial temporary solution $b_{ij}\in\{0,1\}$ is derived from (19) by considering all Lagrange multipliers equal to zero (i.e., the weighted utility equals to the utility, so that each user is assigned to the "best" BS irrespective of its load). Then, multipliers associated to BSs that would exceed available resources are iteratively increased in a smart way until a feasible solution, if exists, is found. The increase of multipliers cause the reassignment of users from most loaded BSs to less loaded ones. For instance, assume that for a given set of fixed multipliers, BS j* has the highest radio resource constraint violation, that is $\pi_j*\geq\pi_j$ for j=1…N. So, attending to (19), the reassignment of a given user i from BS j* to BS j could lead to a better solution if $w_{ij} > w_{ij}$* is hold, which can be achieved by incrementing the multiplier value belonging to the most offending constraint in BS j*.

V. Performance Evaluation

We consider a cellular layout of 19 hexagonal cells (one central cell and two tiers). A single frequency channel with 10MHz of bandwidth and a frequency reuse pattern of 3 are considered. The maximum transmission power of all BSs is limited to 43 dBm and their transport capacity is expressed in terms of the transport capacity factor ϕ. User terminals are assumed to be uniformly distributed over the entire service area. All users are assumed to have the same downlink data transmission rate requirement R_i^{min}. However, users exceeding a given maximum radio cost α_{ij}^{max} are provided with a data rate lower than the required.

We considered that the BS decision-making process must be able to follow channel variations due to propagation path loss and slow shadowing changes. Hence, minimum user rate requirements and resource costs used in the algorithm would represent average values taken over the time scale dictated by long-term channel variations (i.e., few hundreds of milliseconds). Under such an approach, the mean channel gain in each subcarrier k from BS j to user i, referred to $G_{i,j,k}$, is the

TABLE I. MCS THRESHOLDS AND PHY DATA RATES

#	MCS	$SINR_{min}$ (dB)	Data rate (Mbps)
1	BPSK, 1/2	3.4	1.16
2	QPSK, 1/2	6.4	2.33
3	QPSK, 3/4	8.2	3.50
4	16 QAM, 1/2	13.4	4.66
5	16 QAM, 3/4	15.2	7.00
6	64 QAM, 2/3	19.7	9.33
7	64 QAM, 3/4	21.4	10.50

same for all subcarriers and will be simple denoted as $G_{i,j}$. This approach does not preclude the applicability of the proposed algorithm in a problem also tackling fast fading fluctuations in the channel gain, e.g., a joint scheduling and BS assignment problem. In any case, this alternative approach is out of the scope of the current work that mainly tries to expose the benefits (or needs) to incorporate both radio and transport information in the ordinary BS assignment problem. Therefore, the computation of $SINR_{i,j,k}$ according to (1) leads also to the same value for all subcarriers, namely $SINR_{i,j}$, since the interference levels are assumed to be uniformly distributed over the entire bandwidth, as argued previously and captured by (14). So, upon the average $SINR_{i,j}$, the modulation and coding scheme (MCS), and, consequently the corresponding achievable rate at the air interface, are taken from the look-up table provided in Table 1.

Propagation losses are computed using the COST-231 Hata model [18] with parameters as provided in Table 2. Shadowing is modeled with an 8 dB log-normal standard deviation for shadowing effect and spatial shadowing correlation of 50%. The radius of the cell has been chosen so that a signal to noise ratio SNR_{req} = 3.4 dB is assured at the cell border with a probability of 95%, considering typical sample link budgets for mobile broadband systems [18]. All system parameters are summarised in Table 2.

A. Evaluated BS Assignment Algorithms

We evaluate the performance of three different BS assignment algorithms:

- *Algorithm A* is a basic minimum path loss (MPL) approach that assigns each user to the BS with highest channel gain. Notice that, in case of full load conditions, *Algorithm A* would also be equivalent to an algorithm that assigns a user to the BS that provides the highest SINR.
- *Algorithm B* takes into consideration the radio load of BSs. *Algorithm B* is implemented by an straightforward adaptation of the algorithm described in previous section so that only radio resource constraints are considered in the assignment process (i.e., Lagrange multipliers associated to transport constraints are set to zero, and thus transport costs are forced to zero).
- *Algorithm C* represents an enhancement of *Algorithm B* as it considers both radio and transport load of BSs to determine the BS assignment solution. *Algorithm C* is realized by means of the proposed BS assignment approach.

TABLE II. OFDMA SYSTEM PARAMETERS

Parameter	Value
Total number of cells	19
Max. BS transmission power	43 dBm
Transmit antenna gain	18 dBi
Cell radius, R	1.3 Km
Antenna pattern	Omnidirectional
Operating frequency, f	2500 MHz
Reuse factor	3
Channel bandwidth, BW	10 MHz
Number of data subcarriers	720
OFDM symbol duration	102.9 μs
Path loss model	COST-231 Hata
BS height, h_b	32 m
Mobile terminal height, h_m	1.5 m
Shadowing standard deviation	8 dB
Shadowing correlation	50%
Shadow fade margin	13.2 dB
Thermal noise	-174 dBm/Hz
Receiver noise figure	7 dB
User rate requirements, R_i^{min}	200,400 Kbps
Maximum radio cost, α_{ij}^{max}	0.2

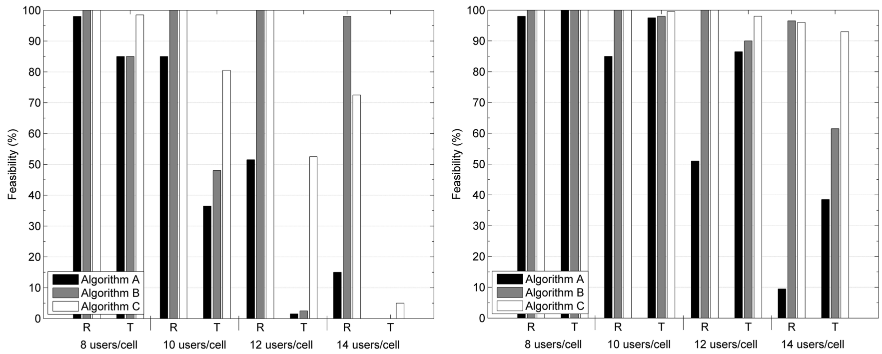
The evaluation of the three algorithms is performed as follows. For a given snapshot of the system (i.e., random distribution of M users in the service area), a BS assignment solution for all the users is computed with each algorithm. For each of the obtained solutions, an accurate estimation of the real interference levels and consequently resource consumptions is undertaken by using a recursive algorithm such as the one proposed by Yates [19] to solve power levels under a fixed BS assignment. This step is needed to allow a fair comparison of the different schemes. At this regard, the real co-channel interference would be less than or equal to the maximum one considered in (14) when assuming a fully-loaded system. An estimation of this real co-channel interference $\tilde{I}_{i,j,k}$ can be expressed as:

$$\tilde{I}_{i,j,k} = \sum_{n=1,n\neq j}^{n=N_k} G_{i,j,k} \frac{P_n^{max}}{K_n} \theta_n \le \sum_{n=1,n\neq j}^{n=N_k} G_{i,j,k} \frac{P_n^{max}}{K_n} = I_{i,j,k}^{max} \quad (20)$$

where θ_n denotes the radio interface's real load level of the interfering BS n, computed as:

$$\theta_n = \frac{\sum_{i=1}^{M} \tilde{\alpha}_{in} b_{in}}{\max(1, \sum_{i=1}^{M} \tilde{\alpha}_{in} b_{in}, \sum_{i=1}^{M} \beta_{in} b_{in})} \quad (21)$$

where $\tilde{\alpha}_{in}$ denotes the real radio cost (i.e., obtained from (4) using the real load level, unlike the value of α_{in} considered in the algorithm logic that assumes full-load). Starting from full load conditions (i.e., initial values for θ_n are set to one), at each iteration, correspondent radio costs are computed and a new value for θ_n is obtained from (21) until the algorithm converges (notice that convergence is always achieved by not allowing values for θ_n greater than one). It is worth clarifying that in order to avoid the border effect in the characterization of the



(a) (b)

Figure 2. Radio (R) and transport (T) feasibility as function of mean users/cell for data rate requirement R^{min}=200Kbps and transport capacity factor: (a) ϕ=0.3; (b) ϕ=0.4.

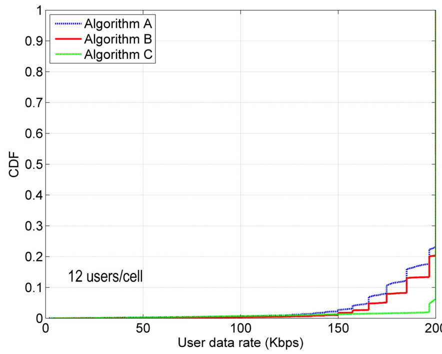
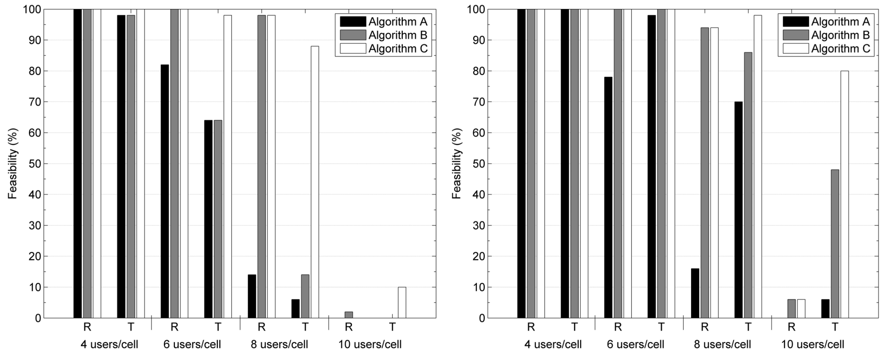


Figure 3. Rate degradation of each BS assignment algorithm for R^{min}=200Kbps and ϕ=0.3.



(a) (b)

Figure 4. Radio (R) and transport (T) feasibility as function of mean users/cell for data rate requirement R^{min}=400Kbps and transport capacity factor: (a) ϕ=0.4; (b) ϕ=0.5.

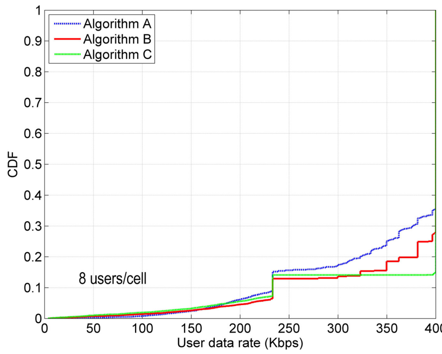


Figure 5. Rate degradation of each BS assignment algorithm for R^{min}=400Kbps and ϕ=0.4.

real interference, we consider two additional tiers of cells that are assumed to have a fixed air interface load of $\theta_n = 0.5$.

B. Simulation Results

Fig. 2 presents the feasibility percentage observed on each resource constraint under different distribution of users/cell, rate requirements R^{min}=200Kbps and transport capacity ϕ={0.3, 0.4}. For each BS assignment solution provided by the algorithms we verify the feasibility of satisfying each resource type, i.e., radio and transport constraints, considered in (9) and (10), respectively. The feasibility percentage is obtained over a total of 10000 snapshots. In Fig. 2 (a) we consider a transport capacity factor ϕ=0.3 for all the BSs in the system. In case of 8 users per cell, we can observe that while solutions provided by the algorithms in general suffice air interface resources of BSs (i.e., feasibility of 100%, except for *Algorithm A* that achieves 98%), the transport constraint constitutes the more restricted resource as lower feasibility can be provided by the algorithms. Notice that in this case the overall feasibility of the solutions delivered by the algorithms is mainly driven by transport capacity rather than air interface restrictions. Under such capacity restriction, *Algorithm C* provides an increase in the feasibility on the transport constraint of around 10% respect to the other algorithms. This is because *Algorithm C* considers transport resources on the assignment selection, and it is more likely to provide a BS assignment configuration that may result in a feasible assignment from the transport standpoint. In Fig. 2 (b) we replicate the same scenario but now considering a transport capacity factor ϕ=0.4, where we can see that for 12 and 14 users per cell, transport resources still represent a capacity restriction for algorithms *B* and *C*.

In the case of *Algorithm A* it is observed that it leads to a lower feasibility on the radio constraint, suggesting that this algorithm demands a higher amount of radio resources. It is worth clarifying that when a feasible BS assignment solution cannot be found by a BS assignment algorithm, degradation of users' data rate is consequently produced due to insufficient resources at the BSs to satisfy user rate requirements. In order to quantify the extent of this service degradation, we compare the three BS assignment algorithms in terms of the percentage of users that are provided a given data rate. In this sense, Fig. 3 shows the data rate degradation produced by each algorithm when considering a transport capacity factor of ϕ=0.3, with a distribution of 12 users per cell and a data rate requirement of R^{min}=200 Kbps. Rate degradation of each user is computed by considering that each BS exceeding its radio and/or transport resources proportionally reduces the rate allocated to each served user. It is observed that *Algorithm A* exhibits the highest data rate degradation, so that it is able to guarantee the requested minimum data rate to around 75% of the total users. Lower data rate degradation is observed with algorithms *B* and

C, where they can satisfy the minimum rate requirement for around 78% and 92%, respectively.

Fig. 4 depicts feasibility results obtained when considering a higher data rate requirement R^{min}=400Kbps, under transport capacity factors (a) ϕ=0.4, and (b) ϕ=0.5. We can see that in the first case the transport constraint constitutes the most restricted condition. For instance, in Fig. 4 (a) notice that for 8 users per cell the percentage of solutions satisfying both radio and transport constraints provided by *Algorithm C* is around 90%, whereas algorithms *A* and *B* achieves 7% and 15%, respectively.

Furthermore, for the same load of users per cell, *Algorithm B* requires 10% more of additional transport capacity in order to achieve performance close the provided by *Algorithm C*. That is, the BS assignment solutions found by *Algorithm B* satisfy both radio and transport constraints in around 85% of the cases when considering a transport capacity factor ϕ=0.4, as shown in Fig. 4 (b). Finally, Fig. 5 provides the rate degradation produced as a result of resource limitations on the BSs. As before, *Algorithm C* is able to guarantee the data rate required to a higher number of users in the system.

VI. CONCLUDING REMARKS

In this paper we have developed a BS assignment algorithm that, unlike most of the existing mechanisms, it accounts for potential backhaul network constraints in the BS decision making process of an OFDMA-based cellular network. A utility-based and resource cost framework has been used to map the BS assignment problem to a MMKP and a heuristic algorithm with polynomial time complexity has been used to solve the problem. Simulation results shown that, in scenarios with limited transport capacity (i.e., scenarios where the transport capacity is less than half of the peak rate in the radio interface), the proposed algorithm brings up significant gains with respect to algorithms that are completely based on radio criteria in terms of the number of feasible BS assignment solutions it can determine, as well as in terms of the percentage of users that can be served guaranteeing their minimum bit rate constraints.

ACKNOWLEDGMENT

This work has been developed within the scope of TelMAX Project (www.proyectotelmax.es) (CENIT Nº 20071036, partially funded by CDTI of the Spanish Ministry of Science and Innovation under the INGENIO 2010 Program) and COGNOS grant (TEC2007-60985, supported by the Spanish Research Council and FEDER funds).

REFERENCES

[1] Guoqing Li and Hui Liu, "Downlink Radio Resource Allocation for Multi-Cell OFDMA System", IEEE Trans. Wireless Commun., vol. 5, no. 12, pp. 3451-3459, Dec. 2006.

[2] S. Pietrzyk, G. J. M. Janssen, "Radio Resource Allocation for Cellular Networks Based on OFDMA with QoS Guarantees", in Proc. Global Commun. Conf. (GLOBECOM), Dec. 2004.

[3] A. Alsawah, I. Fijalkow "Base-Station and Subcarrier Assignment in Two-Cell OFDMA Downlink under QoS Fairness", in Proc. Int. Symposium on Personal Indoor and Mobile Radio Communications (PIMRC), 15-18 Sept. 2008.

[4] K. W. Choi, W. S. Jeon, D. G. Jeong, "Resource Allocation in OFDMA Wireless Communications Systems Supporting Multimedia Services", IEEE/ACM Trans. Netw., vol. 17, no. 3, pp. 926 - 935, June 2009.

[5] R. Y. Chan, Z. Tao, J. Zhang, C. C. J. Kuo, "Multicell OFDMA Downlink Resource Allocation Using Graphic Framework", IEEE Trans. Veh. Technol., vol. 58, no. 7, pp. 3494-3507, Sep. 2009.

[6] A. Bolle, H. Herbertsson, "Backhaul must make room for HSDPA", Wireless Europe, no. 43, pp. 17-18, March 2006.

[7] NGMN Alliance, "Optimised Backhaul Requirements", White Paper v3.0, Aug. 2008, available at http://www.ngmn.org.

[8] K. Ayagari and J. Tang, "Backhaul Solutions for 3G Networks", Alcatel-Lucent White Paper, 2007.

[9] S. Nádas, S. Rácz, Z. Nagy, S. Molnár, "Providing Congestion Control in the Iub Transport Network for HSDPA", in Proc. Global Commun. Conf. (GLOBECOM), 26-30 Nov. 2007.

[10] 3GPP TR 25.902 V7.1.0, "Iub/Iur congestion control" (Release 7), March 2007.

[11] J. Lakkakorpi, A. Sayenko, "Backhaul as a Bottleneck in IEEE 802.16e Networks", in Proc. Global Communications Confer-ence (GLOBECOM), 30 Nov.-4 Dec. 2008.

[12] W. H. Kuo, W. Liao, "Utility-based Radio Resource Allocation for QoS Traffic in Wireless Networks", IEEE Trans. Wireless Commun., vol. 7, no. 7, July 2008.

[13] H. Kellerer, U. Pferschy, and D. Pisinger, Knapsack Problems. Springer-Verlag, 2004.

[14] M. Moser, D. P. Jokanovic, and N. Shiratori, "An Algorithm for the Multidimesional Multiple-choice Knapsack Problem", IEICE Trans. Fundamentals Electronics, Commun. and Computer Sciences, vol. E80-A, no. 3, March 1997.

[15] M. Katoozian, K. Navaie, and H. Yanikomeroglu, "Optimal Utility-Based Resource Allocation for OFDM Networks with Multiple Types of Traffic", in Proc. of Semi-annual IEEE Vehicular Tech. Conf., 11-14 May 2008.

[16] H. Galeana, F. Novillo, R. Ferrús, "A Cost-based Approach for Base Station Assignment in Mobile Networks with Limited Backhaul Capacity", in Proc. Global Commun. Conf. (GLOBECOM), 30 Nov-4 Dec. 2008.

[17] H. Everett, "Generalized Lagrange Multiplier Method for Solving Problems of Optimum Allocation of Resources", Operations Research, vol. 2, 1963.

[18] K. Ramadas and R. Jain, WiMAX System Evaluation Methodology. Tech. Report, Wimax Forum, Dec. 2007.

[19] R. D. Yates, "A Framework for Uplink Power Control in Cellular Radio Systems", IEEE J. Sel. Areas Commun., vol. 13, no. 7, pp. 1341-1347, Sep. 1995.