# A Cost-based Approach for Base Station Assignment in Mobile Networks with Limited Backhaul Capacity

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*Abstract*— **Existing base station (BS) assignment methods in cellular networks are mainly driven by radio conditions since it is assumed that the limiting factor is the air interface. This assumption has been proven to be very reasonable when circuit voice was the dominant service and backhaul capacity provisioning in BS accounting for the peak rate of the radio link was an economically feasible option. However, as traffic continues increasing and enhanced air interfaces are been deployed, a growing concern is that also the mobile backhauling can become a bottleneck in certain deployment scenarios. In this paper we present a BS assignment algorithm designed to optimize radio resource usage while simultaneously considering potential capacity limitations in mobile backhauls. The BS assignment problem is formulated using a cost-based framework and mapped into a Multiple-Choice Multidimensional Knapsack Problem (MMKP) that is solved by means of a heuristic algorithm with polynomial time. The proposed algorithm is evaluated and compared to two schemes based exclusively on radio conditions. Simulation results show that the proposed algorithm can assign more users than existing algorithms without violating radio and transport constraints in partially backhaul limited scenarios.**

## I. INTRODUCTION

Wireless access technologies has been evolving rapidly in recent years, providing higher data rates and paving the way for ubiquitous, high speed broadband wireless coverage. This fact, as well as the pervasive increase of data services and the number of mobile user, intensifies the need of extra bandwidth in the backhaul network to support the increased traffic. The main challenge, however, is how to effectively face new bandwidth requirements in mobile networks, especially because the backhaul is one of the major contributors to the high costs of building out and running a mobile network. The backhaul is the infrastructure in the radio access network (RAN) that interconnects base stations (BS) with network controllers or switching equipments in the core network. As most of current 2G/3G backhaul networks are realized by means of point-to-point T1/E1 links, there is a growing concern that existing backhaul technologies are fast becoming a bottleneck as wireless access speeds increase [1]. For instance, the move towards enhanced air interface technologies, such as High Speed Data Packet Access (HSDPA), means that cell sites are likely to increase seventh times their current capacity requirements [2]. On the other hand, faster technologies such as fiber connections can be still expensive to lease or install in a number of scenarios in the backhaul. Hence, it should not be precluded the idea that in some situations the network may be limited by the backhaul transmission network, rather than the wireless link.

Over such a basis, in a previous work [3] we proposed a BS assignment strategy where information about the available capacity in the backhaul network is considered in the decision making process of assigning mobile users to BSs. This leads to a new paradigm where transport resources are taken into consideration not only at the network dimensioning stage but are included in an integrated and dynamic resource management framework. Thus, in this paper we extend that work by formulating the proposed BS assignment strategy as an optimization problem. We use a cost-based framework to reflect the amount of network resources that a given BS assignment strategy demands from both the air interface and transport network. The optimization problem is mapped into a Multiple-Choice Multidimensional Knapsack Problem (MMKP) and solved by means of a heuristic algorithm with polynomial time. In simulations we compare our proposed BS assignment algorithm that accounts for potential backhaul constraints, with two different algorithms that are exclusively driven by radio conditions. Specifically, the first benchmark algorithm aims to minimize the cost at the air interface in terms of the required transmission power, while the second approach assign users according to the classical minimum path loss criterion. In this context, it will be shown that employing backhaul-aware BS assignment algorithms, the impact of a partially limited backhaul scenario can be diminished by conveniently re-allocating some users to other BSs with available resources in both air interface and transport network links. We focus our analysis on the provisioning of delay sensitive services where it is particularly important to guarantee a given data rate in both air interface and transport network simultaneously.

The rest of the paper is organized as follows. In section II, we present the motivation of our approach and a generic framework where BS assignment strategies considering backhaul constraints can be applied. Section III presents the system model and costs framework definition. This is followed by the formulation of the optimization problem and the mapping into an MMKP in section IV. Section V describes the used heuristic search algorithm. The performance of the

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proposed BS assignment algorithm is studied in section VI. Finally, conclusions are summarized in section VII.

## II. Motivation

In a typical RAN deployment the infrastructure involved in the backhaul network is very complex since there could be hundreds of cell sites that need to be interconnected using different topologies and transmission technologies. Furthermore, a RAN deployment is likely to have multiple cell coverage in some locations of the service area, and overlapping coverage areas of nearby BSs provide some users with more than one candidate BS. In this context, methods for allocating users in cellular networks has attracted considerable attention (e.g. see [4], [5]), but generally this problem has been formulated in terms of air interface resource optimization without considering backhaul constraints of the BSs. It is worth noting that when addressing BS assignment strategies that consider criteria other than radio, the main challenge is to keep under control the amount of degradation of the radio interface due to not always connecting users to their "best" radio serving BS (e.g. increased path loss and higher interference level) so that the overall performance can be definitively enhanced (e.g. higher number of connections can be served satisfying both radio and transport constraints).

In this work, we concentrate in a partially limited RAN scenario with a single radio access technology (RAT) and frequency reuse factor of one, which is claimed to be the most critical in terms of using information other than radio metrics to control the BS assignment process. Notice that in scenarios with multiple frequency layers or heterogeneous RAT's, mobile users can be assigned to a given frequency layer or RAT considering backhaul constraints as well, but the total or partial decoupling of the radio resource pools used in each frequency/RAT could make this decision less critical in term of radio degradation.

## III. System Model

For the reasons stated in previous section, the performance analysis of backhaul-aware BS assignment strategies will be addressed considering a single frequency WCDMA network deployment scenario. Specifically, we focus on the downlink because it is usually considered the more restrictive link due to the asymmetric bandwidth demand between the downlink and the uplink data services.

We consider a network consisting of $N$ BSs that cover a geographical area in which at a given instant there are $M$ active users. The system state is characterized by a $M$ x $N$ matrix, hereafter referred to as B = $\{b_{ij}\}$, that denotes the BS assignments. In particular, $b_{ij} = 1$, if BS $j$ is assigned to user $i$, and $b_{ij} = 0$, otherwise. Each active user is required to be served by a BS so that a given bit rate is guaranteed both in the air interface and in the transport network. To that end, the suitability of a given assignment is assessed by means of computing two resource cost metrics: (a) a radio cost depending on the transmission power required in the air interface and, (b) a transport cost depending on the required bit rate in the transmission network. The exact formulation for these two resource cost metrics are given in next subsections.

### A. Air Interface Costs

In the downlink the required transmitted power $P_{ij}$ for user $i$ being served by BS $j$ can be expressed as [6]:

$$P_{ij} = \frac{\frac{R_i}{W}\left(\frac{E_b}{N_0}\right)_i}{\left(1+\frac{R_i}{W}\left(\frac{E_b}{N_0}\right)_i(1-\rho_i)\right)}\left((1-\rho_i)P_j + \sum_{k=1,k\neq j}^{N}\frac{L_{ij}}{L_{ik}}P_k + L_{ij}P_N\right) \quad (1)$$

where $(E_b/N_0)_i$ is the minimum bit energy over noise power spectral density requirement, $P_{i,j}$ is the required transmit power devoted to user $i$ being served by BS $j$, $P_N$ is the noise power at the user terminal, $R_i$ is the bit rate for the user $i$, $W$ is the chip rate, $P_k$ is the total transmit power of BS $k$, $L_{ik}$ is the path loss between BS $k$ and user $i$, and $\rho_i$ is the orthogonality factor seen by user $i$ ($\rho_i = 1$ means perfect orthogonality).

Denoting the maximum available transmission power for data channels in BS $j$ as $P_j^{\max}$, the radio cost of assigning user $i$ to BS $j$ can be formulated as follows:

$$\alpha_{ij} = \frac{P_{ij}^{max}}{P_j^{max}} \quad (2)$$

where $P_{ij}^{max}$ is obtained using (1) and assuming that all BSs are transmitting at maximum transmission power. In this sense, note that $\alpha_{ij}$ represents the fraction of the total transmission power that would be required under the assumption of full load. This assumption is needed to be able to define the radio cost so that it is not dependent on a given user's assignment.

### B. Transport Network Costs

In this study transport costs are simply computed as the ratio of the bit rate required by each user to the available transport capacity of the BS, denoted as $C_j^{max}$, where it will be assigned.

$$\beta_{ij} = \frac{R_i}{C_j^{max}} \quad (3)$$

In practical RAN deployments, the transport capacity $C_j^{max}$ provisioned for a given BS is normally dimensioned in accordance to the amount of traffic that this BS can serve over the air interface. In this sense, a common used approach to estimate the air interface downlink capacity is based on the computation of the downlink load factor $n_{DL}$ defined as [7]:

$$\eta_{DL} = \sum_{i=1}^{M_j}\frac{R_i}{W}\left(\frac{E_b}{N_0}\right)_i\left((1-\rho_i)+f_{DL,i}\right) \quad (4)$$

where $M_j$ is the number of users served by BS $j$, $f_{DL,i}$ is the other-to-own cell received power ratio for the $i$-th user. This means that as the load factor move towards one, the downlink capacity approaches to its maximum pole capacity value. Over such a basis, focusing on one important special case where all mobile users have similar characteristics (i.e. service type, bit rate and $E_b/N_0$ requirements), it is easy to show that the maximum value of $C_{air}$ can be estimated using the following expression:

$$C_{air} = M_j \cdot R_i \leq \frac{W}{\left( E_b / N_0 \right)_i ((1-\rho) + f_{DL})} \tag{5}$$

where $\rho = \frac{1}{M_j} \sum_{i=1}^{M_j} \rho_i$ is the average orthogonality factor in the cell and $f_{DL} = \frac{1}{M_j} \sum_{i=1}^{M_j} f_{DL,i}$ is the average ratio of other-to-own cell BS power received by users. Therefore, in our analysis, the transport capacity $C_j^{max}$ of a BS is related to the air interface pole capacity $C_{air}$ by means of a multiplicative factor $\phi$ as shown below:

$$C_j^{max} = \phi \cdot C_{air} \tag{6}$$

A value of $\phi = 1$ would mean that the transport capacity has been dimensioned to satisfy the downlink air pole capacity estimated in the planning process.

## IV. Optimization Problem

### A. Problem Formulation

The BS assignment problem is formulated as an optimization problem where the amount of resources required in the air interface should be minimized whenever radio and transport constraints are guaranteed for all served users. Hence, the optimal BS assignment B = $\{b_{ij}\}$ in a given instant is a solution of the following optimization problem:

$$\max_{ij} \left( \sum_{i=1}^{M} \sum_{j=1}^{N} u_{ij} b_{ij} \right) \tag{7}$$

$$\text{s.t.} \quad \sum_{i=1}^{M} \alpha_{ij} b_{ij} \leq 1 \qquad j = 1,...,N \tag{8}$$

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

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

$$b_{ij} \in \{0,1\} \tag{11}$$

Here $u_{ij}$ denotes the utility of user $i$ being assigned to BS $j$, which is computed for each user as the inverse of the air interface cost $\alpha_{ij}$. The set of constraints in (8) and (9) assures that no more resources than available are assigned to each BS. Note that as we normalize the costs in (2) and (3) the maximum power/transport cost supported by each BS is 1. The third set of constraints in (10) prevents multiple assignments of each user. In order to avoid splitting or partial assignment of users, constraint (11) is used, which however leads to the combinatorial nature of the problem with exponentially growing complexity in the degrees of freedom.

### B. Mapping the Problem into an MMKP

The optimization problem formulated in (7) can be mapped into a Multiple-Choice Multidimensional Knapsack Problem (MMKP) [8]. We consider a cellular network with $N$ BSs as a knapsack with $K = 2N$ dimensions due that each BS involves two resource constraints: maximum power and transport costs. The available resources of the knapsack are represented by $(W_1, W_2, \ldots, W_K)$. Each user $i$ is considered as a group and the BSs in the active set $n_j$ of each user are the items in the group. Each item $j$ of a group $i$ has a particular profit, denoted as $u_{ij}$, and requires different resources from each dimension of the knapsack that is represented by a vector $(w_{ij1}, w_{ij2}, \ldots, w_{ijK})$. The objective of the optimal BS assignment is to exactly select one BS from each group to maximize the total utility, subject to the constraints of the BSs in the network. However, the assignment of all users is in general not always possible, e.g. for a large number of users the system could not have enough resources to serve all of them. Thus, a virtual item is added to each group. This means that all users will have a virtual BS corresponding to a utility and costs equal to zero. If user $i$ does not exist in the optimal solution, it means that was allocated in the virtual BS which means that has not been assigned to the network.

Formally, the MMKP can be stated as follows:

$$\max_{ij} \left( \sum_{i=1}^{M} \sum_{j=1}^{n_j} u_{ij} b_{ij} \right) \tag{12}$$

$$\text{s.t.} \quad \sum_{i=1}^{M} \sum_{j=1}^{n_j} \delta_{ij}^k b_{ij} \leq 1 \qquad k = 1,...,2N \tag{13}$$

$$\sum_{j=1}^{N} b_{ij} \leq 1 \qquad i = 1,...,M \tag{14}$$

$$b_{ij} \in \{0,1\} \tag{15}$$

where $\delta_{ij}^k = {w_{ijk}}/{W_k}$. The formulation of this MMKP problem is equivalent to optimization problem given by equations (7)-(11) considering that for $k$=1,…,$N$ $\delta_{ij}^k \triangleq \alpha_{ij}^k$ and $\alpha_{ij}^k = \alpha_{ij}$ if $k$=$j$, and $\alpha_{ij}^k = 0$ otherwise. And for $k$=$N$+1,…,2$N$ $\delta_{ij}^k \triangleq \beta_{ij}^{k-N}$ and $\beta_{ij}^{k-N} = \beta_{ij}$ if $k$-$N$=$j$ and $\delta_{ij}^k = 0$ otherwise. The variable $b_{ij}$ is equal to 0, implying item $j$ of the $i$th group $M_i$ is not picked, or equal to 1 if item $j$ of the $i$th group $M_i$ is picked.

## V. Heuristic Search Algorithm

Since the problem was formulated as an MMKP, any technique available to solve the MMKP can be used. In particular, there exist two approaches in the literature: exact and heuristic. The exact solution is usually based on branch-and-bound procedures which utilize search trees to find the exact solution. This approach, however, is not suitable for most real-time decision-making applications due to its high computational complexity [4]. The alternative is to use heuristic approaches for MMKP (e.g. [10], [11]) with polynomial time complexity.

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## A. Lagrange Multipliers Theorem

We use a modified version of the algorithm presented in [9] to solve the MMKP through a heuristic approach. The algorithm is based on the Lagrange Multipliers (LM) Theorem proven by Everett [12] and adapted here to our notation to clarify the understanding of our approach.

LM Theorem: Let $\lambda_{1,\ldots,}\lambda_N$ and $\mu_{1,\ldots,}\mu_N$, be $2N$ non-negative Lagrange multipliers, and $b_{ij}^* \in \{0,1\}$ be solution of

$$\max_{ij}\left\{\left(\sum_{i=1}^{M}\sum_{j=1}^{n_j}u_{ij}b_{ij}\right)-\sum_{k=1}^{N}\lambda_k\sum_{i=1}^{M}\sum_{j=1}^{n_j}\alpha_{ij}^k b_{ij}-\sum_{k=1}^{N}\mu_k\sum_{i=1}^{M}\sum_{j=1}^{n_j}\beta_{ij}^k b_{ij}\right\} \quad (16)$$

Then, the binary variables $b_{ij}^*$ are also the solution to

$$\max_{ij}\left(\sum_{i=1}^{M}\sum_{j=1}^{n_j}u_{ij}b_{ij}\right) \quad (17)$$

$$\text{s.t.} \quad \sum_{i=1}^{M}\sum_{j=1}^{n_j}\alpha_{ij}^k b_{ij} \le \sum_{i=1}^{M}\sum_{j=1}^{n_j}\alpha_{ij}^k b_{ij}^* \qquad k=1,\ldots,N \quad (18)$$

$$\sum_{i=1}^{M}\sum_{j=1}^{n_j}\beta_{ij}^k b_{ij} \le \sum_{i=1}^{M}\sum_{j=1}^{n_j}\beta_{ij}^k b_{ij}^* \qquad k=1,\ldots,N \quad (19)$$

According to this theorem, the solution to the unconstrained optimization problem (16) is also a solution to the constrained optimization problem (17) which is our MMKP with (13) replaced by $\sum_{i=1}^{M}\sum_{j=1}^{n_j}\alpha_{ij}^k b_{ij}^*$ and $\sum_{i=1}^{M}\sum_{j=1}^{n_j}\beta_{ij}^k b_{ij}^*$. Thus, if the multipliers $\lambda_k$ and $\mu_k$ are known, the optimization problem is easily solved, and problem (16) can be rewritten as

$$\max_{ij}\left\{\sum_{i=1}^{M}\sum_{j=1}^{n_j}(u_{ij}-\sum_{k=1}^{N}\lambda_k\alpha_{ij}^k-\sum_{k=1}^{N}\mu_k\beta_{ij}^k)b_{ij}\right\} \quad (20)$$

which in turn implies that the solutions are

$$b_{ij}^*\begin{cases}1 & \text{if} \quad w_{ij}=u_{ij}-\lambda_j\alpha_{ij}-\mu_j\beta_{ij}>0\\ 0 & \text{otherwise}\end{cases} \quad (21)$$

where $w_{ij}$ is defined as the weighting utility. Therefore, the only step to do is to compute the Lagrange multipliers. It is worth noting that if these multipliers are computed such that the $2N$ terms $1-\sum_{i=1}^{M}\sum_{j=1}^{n_j}\alpha_{ij}^k b_{ij}^*$ and $1-\sum_{i=1}^{M}\sum_{j=1}^{n_j}\beta_{ij}^k b_{ij}^*$ are non-negative, the solution is feasible. Finally, constraint (14) not considered in Everett's theorem, can be easily taken into account by selecting the $b_{ij}$ in equation (21) that provides the maximum weighted utility for each user.

## B. Description of the Heuristic Algorithm

The algorithm has three main phases, as shown in Table 1. The *Drop* and *Add* phases aim to adjust BS assignments until constraints are satisfied and the maximum utility can be achieved. After these phases some users could have been allocated into the virtual BS. Therefore, in *Relaxation* phase we allow constraints to be relaxed in order to reassign those users to a BS present in its active set.

The algorithm starts in s0.1 by setting the Lagrange multipliers to zero. In s0.2 the costs associated with the air interface and transport network are normalized and user utilities are computed. To produce an initial BS assignment, in s0.3 the most valuable BS for each user are selected, whereas in s0.4 constraint violations are computed. If constraints are violated, the initial BS assignments need to be adjusted in the Drop phase until constraints can be fulfilled. Within this phase, Lagrange multipliers are used to decide which user can change its assignment with a less valuable BS from the active set in order to adjust the initial BS assignment. Firstly, the most offending constraint violation is determined in s1.1. Next, we consider in s1.2 the users whose assigned BS correspond to the most offending constraint violation, denoted as $j^*$. For each BS $j$ in the active set of these users, we then compute the increase of the Lagrange multiplier, denoted as $\Delta\lambda_{ij}$ and $\Delta\mu_{ij}$, depending if the most violated constraint is on the radio interface or in the transport network.

Eventually, in s1.3 the user $I^*$ and BS $J^*$ causing the least increase of the corresponding multiplier is chosen for exchange, while Lagrange multiplier $\lambda_{j^*}$ or $\mu_{j^*}$ of the most offending constraint is updated. In step s1.4 the BS assignment matrix and costs associated with the air interface and transport are updated. This new assignment minimizes the gap between the optimal solution and the previous BS assignment solution. The process is repeated until for each user a BS has been assigned and constraints are satisfied.

It is worth noting that the increment to be added to the corresponding multiplier is a value between the least increase and the second least increase, as in this way we prevent a situation where a user could be continuously reassigned between a given pair of BSs (i.e. loops). Moreover, the expressions for determining the increase of multipliers are different from the ones presented in [9], because we assume that the increase of the multiplier for user $i|j(i)=j^*$ is obtained so that its weighting utility in $j^*$ is equal to its weighting utility in BS $j$. Doing this we deduce the expressions for the increase of multipliers.

After completion of the Drop phase, there may be some space left in the knapsack. This space may be utilized to improve the solution by replacing some assignments with more valuable ones. Therefore, in Add phase, each BS $k$ in the active set of each user $i$ is checked against the assigned BS $j$ of that user. It is verified whether BS $k$ is more valuable than BS $j$, and if it can replace the currently assigned BS without violating the constraints of the knapsack. This is done by computing the utility increment, denoted as $\Delta u_{ij}$, for each user in s2.1. Among all exchangeable users, in s2.2 user $I'$ is selected, so that replacing its previously assigned BS by a new BS $J'$ causes the largest increase in the total knapsack utility. The exchange is done in s2.3 and the costs associated with the air interface and transport network are updated. This process is repeated until no more exchanges are possible.

After the first two phases of the algorithm, in Relaxation phase, each user $i$ allocated to the virtual BS $j_v$ is reassigned to a BS $j$ present in its active set, otherwise these users would not be served by any BS. The process to decide the new assignment is based on selecting the BS which the corresponding weighting utility $w_{ij}$ is the maximum.

## VI. SIMULATION RESULTS

We consider a cellular deployment with 19 hexagonal cells including a central cell and the cells in its first and second tier. A standard wrap around technique is used to avoid border effects. Users are uniformly distributed in the service area and two different user data rates are considered: 128 Kbps and 384 Kbps. The analysis is conducted using the snapshot technique. Simulation experiments are performed as snapshot evaluations of the system. For each snapshot we solve the optimization problem using the heuristic algorithm. A large number of snapshots are required to obtain accurate average values. Simulation parameters are summarized in Table 2. The downlink pole capacity $C_{air}$ provided in Table 2 was obtained by rounding expression (5) to the nearest multiple of the bit rate under consideration and assuming an average ratio of other-to-own interference $f_{DL}$=0.65 and average orthogonality factor $\rho$ = 0.5 [6]. This pole capacity is used in our analysis to set up the transport capacity of BSs according to (6). The performance of the following 3 BS assignment strategies are evaluated and compared:

- *Backhaul-aware strategy*: aimed to minimize the costs at the air interface while taking into account potential backhaul restrictions in the BS assignment process. This strategy is realized by means of the heuristic algorithm, considering that each BS has two constraints: air interface and transport network costs.
- *Radio-based strategy*: As previous one, this strategy is aimed at minimizing air interface costs but considering the power as the unique constraint of each BS.
- *Minimum Path Loss (MPL) strategy*: assignments are based on selecting the BS with minimum radio path loss.

The strategies are compared in terms of the number of active users that can be effectively allocated to BSs so that both radio and transport constraints are satisfied in the 95 % of the cases. In this sense, using the BS assignment solution delivered by the heuristic algorithm, the total transmission power and the aggregated rate of each BS can be computed, and from these values the percentage of users that satisfy both constraints can be obtained. Simulation results are presented in Fig. 1 and Fig. 2 for 128 Kbps and 384 Kbps, respectively.

TABLE 1. HEURISTIC ALGORITHM

**s0. Initialization and normalization**

s0.1: Initialize Lagrange Multipliers (LM)
$\lambda_k \leftarrow 0$, $\mu_k \leftarrow 0$
s0.2: Normalize costs and compute user utilities
$$\alpha_{ij} = \frac{P_{ij}}{P_j},\ \beta_{ij} = \frac{R_i}{C_j},\ u_{ij} = \frac{1}{\alpha_{ij}}$$
s0.3: **for** each user $i$ the most valuable BS $j$ is assigned
$j(i)$ = argmax$\{u_{ij}\}$ and $b_{ij} \leftarrow 1$
s0.4: Compute the resource constraint violations for all $j$:
$$\pi_j = \sum_{i=1}^{M} \alpha_{ij} b_{ij},\ \tau_j = \sum_{i=1}^{M} \beta_{ij} b_{ij},\ \psi_j = \{\pi_1, .., \pi_j, \tau_1, .., \tau_j\}$$

**s1. Drop phase**

**while** ($\psi_j > 1$ for any $j$) **do**
s1.1: Most offending constraint violation: $j^* = \arg\max_j \{\psi_j\}$
s1.2: Compute the increase $\Delta\lambda_{j^*,ij}/\Delta\mu_{j^*,ij}$ of the LM $\lambda_{j^*}/\mu_{j^*}$ for the most offending radio/transport constraint.
**for** $\{i|\, j(i) = j^*\}$
**for** $\{j = 1{:}n_j\}$
**if** *radio* **then**
$$\Delta\lambda_{j^*,ij} \leftarrow \frac{u_{ij^*} - u_{ij} - \lambda_{j^*}\alpha_{ij^*} + \lambda_j\alpha_{ij} - \mu_{j^*}\beta_{ij^*} + \mu_j\beta_{ij}}{\alpha_{ij^*}}$$
**else**
$$\Delta\mu_{j^*,ij} \leftarrow \frac{u_{ij^*} - u_{ij} - \lambda_{j^*}\alpha_{ij^*} + \lambda_j\alpha_{ij} - \mu_{j^*}\beta_{ij^*} + \mu_j\beta_{ij}}{\beta_{ij^*}}$$
**end if**
**end for**
**end for**
s1.3: Find the user to be changed its assignment and re-evaluate LMs
**if** *radio* **then**
$I^*J^*$ = arg min$_{ij}$ $\{\Delta\lambda_{j^*,ij}\}$, $I''J''$ = arg min$_{ij}$ $\{\Delta\lambda_{j^*,ij}\}$, $I^* \neq I''$
$$\lambda_{j^*} \leftarrow \lambda_{j^*} + \frac{\Delta\lambda_{I^*J^*} + \Delta\lambda_{I'J'}}{2}$$
**else**
$I^*J^*$ = arg min$_{ij}$ $\{\Delta\mu_{j^*,ij}\}$, $I''J''$ = arg min$_{ij}$ $\{\Delta\mu_{j^*,ij}\}$, $I^* \neq I''$
$$\mu_{j^*} \leftarrow \mu_{j^*} + \frac{\Delta\mu_{I^*J^*} + \Delta\mu_{I'J'}}{2}$$
**endif**
s1.4: Exchange the selected user and update constraints
$b_{I^*j(I^*)} \leftarrow 0$, $b_{I^*J^*} \leftarrow 1$,
$\pi_{j^*} \leftarrow \pi_{j^*} - \alpha_{I^*j^*}$, $\tau_{j^*} \leftarrow \tau_{j^*} - \beta_{I^*j^*}$,
$\pi_{J^*} \leftarrow \pi_{J^*} + \alpha_{I^*J^*}$, $\tau_{j^*} \leftarrow \tau_{j^*} + \beta_{I^*J^*}$,
**end while**

**s2. Add phase**

**while** more assignments can be exchanged **do**
s2.1: Compute utility increases $\Delta u_{ij}$
**for** $\{i = 1{:}M\}$
**for** $\{k = 1{:}n_j\}$
$$\Delta u_{ij} \begin{cases} u_{ik} - u_{ij} & \text{if } u_{ik} - u_{ij} > 0,\ \pi_k + \alpha_{ik} \le 1,\ \tau_k + \beta_{ik} \le 1 \\ 0 & \text{otherwise} \end{cases}$$
**end for**
**end for**
s2.2: Find the best exchangeable assignment
$I'J'$ = argmax$_{ij}\{\Delta u_{ij}\}$
$b_{I'j(I')} \leftarrow 0$, $b_{I'J'} \leftarrow 1$,
s2.3: Update constraints
$\pi_{j(I')} \leftarrow \pi_{j(I')} - \alpha_{I'j(I')}$, $\tau_{j(I')} \leftarrow \tau_{j(I')} - \beta_{I'j(I')}$,
$\pi_{J'} \leftarrow \pi_{J'} + \alpha_{I'J'}$, $\tau_{J'} \leftarrow \tau_{J'} + \beta_{I'J'}$
**end while**

**s3. Relaxation phase**

s3.1: Reassign users from BS $j_v$ to the BS with maximum weighting utility
**for** $\{i|\, j(i) = j_v\}$
**for** $\{j = 1{:}n_j\}$
$$w_{ij} = u_{ij} - \lambda_j\alpha_{ij} - \mu_j\beta_{ij}$$
**end for**
$ij$ = argmax$_{ij}\{w_{ij}\}$
$b_{ijv} \leftarrow 0$, $b_{ij} \leftarrow 1$
**end for**

The assignment strategies are analyzed in scenarios with partially limited backhaul capacity. In this sense, the x-axis of the graphs shows the percentage of BSs with transport limitations. Notice that two different limited transport capacity values are represented by means of the $\phi$ factor, which is the ratio of the backhaul capacity to the air interface capacity. Focusing on Fig. 1, it can be seen that the backhaul-aware BS assignment strategy outperforms the benchmark strategies since it is able to allocate more users that can satisfy both radio and transport constraints. Specifically, it provides a gain of about 12 % with respect to the radio-based strategy in a scenario where around 10 % of BSs have limited transport capacity ($\phi$ = 1). On the other hand, for a limited transport capacity value equivalent to $\phi$ = 1.5 it still obtaining gains with respect to radio-based strategy. This is because the backhaul-aware strategy takes advantage of the available backhaul capacity and tries to distribute users among BSs in order to balance the usage of the transport network. It can be seen also that a common assignment approach such as MPL provides lower performance than the backhaul-aware and radio-based strategies. When considering higher data rates such as 384 Kbps (see Fig. 2) the strategies behaves similar that in the previous case, but the obtained gains increase. For instance, the gain achieved by the backhaul-aware strategy is about 14 % when compared to radio-based strategy in a scenario with 10 % of the BSs with limited capacity ($\phi = 1$).

TABLE 2. SIMULATION PARAMETERS

| Parameter | Value |
|---|---|
| Bit rate, $R_i$ | 128, 384 Kbps |
| $Eb/N_0$ target | 5.3, 5.2 dB |
| Pole capacity, $C_{air}$ | 1024, 1152 Kbps |
| Cell radius | 1 Km |
| Propagation model | L(dB)=128.1+37.6log[d(km)]+S(dB) |
| Shadowing standard deviation, $S$ | 10 dB |
| Chip rate, $W$ | 3.84 Mchips/s |
| BS max. transmitted power | 43 dBm |
| Noise power, $P_N$ | -101.15 dBm |

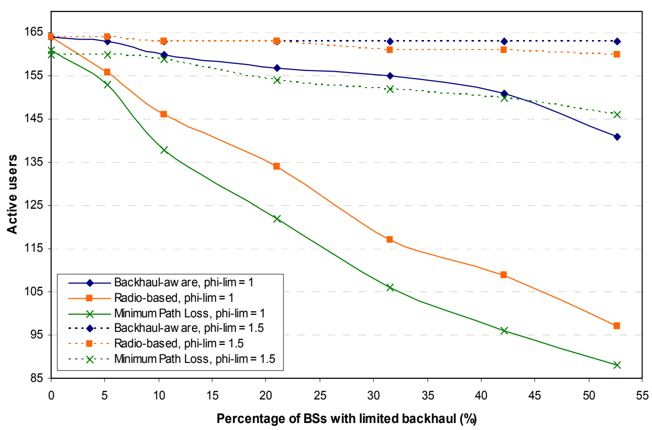


Fig. 1. Maximum assignable users with service rate 128 Kbps as function of the percentage of BSs with limited backhaul ($\phi_{lim}$=1 and $\phi_{lim}$=1.5). The rest of BSs have unlimited backhaul capacity ($\phi_{unlim}$=3).

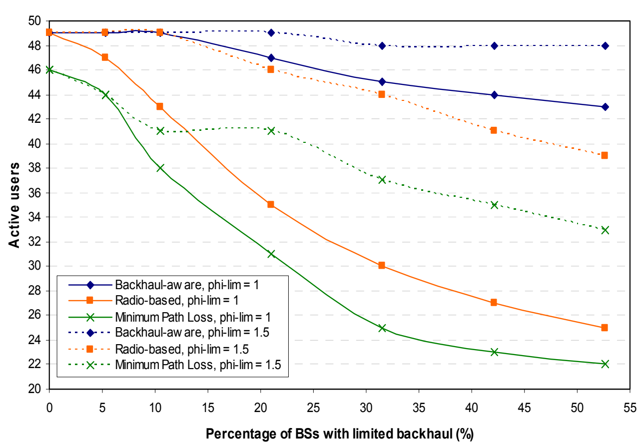


Fig. 2. Maximum assignable users with service rate 384 Kbps as function of the percentage of BSs with limited backhaul ($\phi_{lim}$=1 and $\phi_{lim}$=1.5). The rest of BSs have unlimited backhaul capacity ($\phi_{unlim}$=3).

## VII. CONCLUSION

A novel backhaul-aware BS assignment algorithm with polynomial time complexity was proposed in this paper to cope with potential backhaul limitations. The motivation of this approach is the growing concern that the backhaul network can constitute a bottleneck in some RAN deployment scenarios. Simulation results indicates a significant performance improvement in terms of the number of active users that can be effectively assigned to BSs so that both radio and transport constraints are fulfilled in scenarios with partially limited backhaul capacity.

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