Radio Resource Allocation and Green Operation for Mobile Access Networks Based on Radio-over-Fiber

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Abstract—This paper proposes an architecture for mobile wireless networks based on Radio-over-Fiber (RoF) technology. The architecture organizes cells in a multi-tier fashion, with different tiers covering areas with different radii lengths. Proposed optimization algorithm splits cells to improve network capacity in congested areas and merges cells when the demand is low. The evaluation of the effectiveness of the proposed model considered three distinct objectives: minimization of the number of base stations used, maximization of the number of users served, and minimization of network energy consumption. The combination of the first two objectives was also evaluated. Three algorithms based on linear relaxation techniques are introduced for rapid computation of the near-optimum solutions. The proposed architecture is shown to lead to network infrastructures that save costs and energy and yet provide service to a large number of users.

Index Terms—Radio-over-fiber, radio resource management, optimization, mobile networks, integer linear programming, linear relaxation

1 Introduction

The employment of Radio-over-Fiber (RoF) technology can reduce network costs by allowing optimized use of radio resources in mobile wireless networks. It integrates wireless and optic fiber technologies, with the best of each combined in the design of efficient access networks [1], [2], and it is considered to be one of the most promising technologies for the future mobile Internet [3]. In RoF networks, the optical part provides reliable and high-capacity channels, while the wireless part allows user mobility. Such networks involve one or more base station controllers (BSCs) and several remote antenna units (RAUs) attached to a fiber backhaul [4]. Most of the radio frequency (RF) components are centralized at the BSCs, and RAUs are responsible for the electro-optic conversion of RF signals. All radio resources, called base stations (BSs), are located at the BSCs and can be dynamically distributed to allow different configurations so that a broad coverage can be provided at reduced cost [5], [6], [7].

In traditional cellular networks, radio resources are statically allocated and then assigned to users, usually, in a divide-and-conquer approach. Such static system-centric allocation, however, is not efficient for beyond-3G networks, which are supposed to provide ubiquity and high-data rates for a large number of mobile users. Moreover, demand for radio resources changes dynamically as a function of user mobility [8]. User-centric approaches are recently being proposed for the resource allocation of these networks [9], so that these resources can be allocated on demand. In such an approach, radio resources are first allocated on the basis of user demands, and the best base station for the provision of connectivity is then determined.

In the past decade, there has been a tremendous growth in the number of cell phone users accompanied by an exponential increase in traffic in mobile cellular networks. The accelerated adoption of smartphones in 2010 led to a 30-fold increase of traffic in AT&T networks in a period of 12 months [28]. Such unprecedented growth strongly impacts on the energy consumption of cellular networks. Currently, there are approximately 4 millions base stations, each consuming 850 to 1,400 watts with an approximated operational cost of $ 3,000 per year [27]. This cost constitutes a significant portion of operators' expenditures, and it has been a major concern of telecom providers. Indeed, the information and communications technology (ICT) sector is responsible for 2 percent of the world carbon dioxide (CO_2) footprint of which 0.2 percent is due to the operation of mobile networks, with 60 to 80 percent originating from Base Stations (BSs). The radio operation of BSs accounts for 80 percent of the energy consumption of a BS and roughly 90 percent of it wasted as heat [27].

This paper introduces a solution for the user-centric resource allocation problem based on integer linear programming (ILP) formulation. The network considered consists of several Remote antenna units connected by optical links to a base station controller, which has a limited number of radio resources. Solving the problem involves an attempt to determine an optimal distribution of radio

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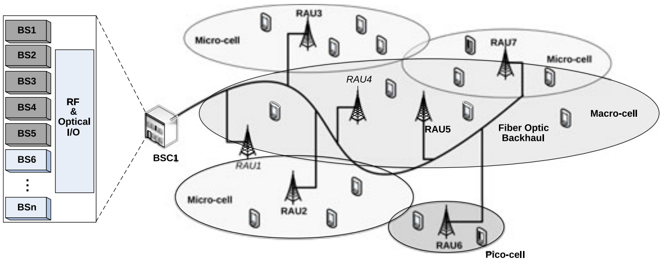


Fig. 1. An example of a scenario employing the architecture proposed.

resources to the RAUs and network cells can be split or merged dynamically to optimize this distribution as a function of the fluctuation of demands. Three distinct objectives are considered: i) minimization of the number of BSs used, which impacts the network cost, ii) maximization of the number of users served, which impacts the total revenue obtained by service providers, and iii) minimization of network energy consumption. The first two objectives are considered together in order to evaluate the trade-offs between them. Three different formulations based on linear relaxation are proposed for the production of solutions in periods shorter than the intervals demanded by integer formulation. The effectiveness of the proposed architecture, as well as of the approximative algorithms based on relaxation are assessed. The proposed approach can be used as a guideline for infrastructure planning and network design to reduce resources demands, improve coverage, or even save energy.

The contribution of this paper differs from those of previous papers designed to save energy by assuming off-the-shelve RoF technology; proposals for dynamic adjustment of cell size assume the existence of automatic adjustment of antenna height [20] which is not a realistic assumption. Other papers that introduce hierarchical architectures based on RoF do not consider mobile users and their demand on access infrastructures [18], [19]. Another unique contribution of this paper is the introduction of fast algorithms for the dynamic configuration of the access network; previous work relies only on time consuming optimization algorithms.

It is evaluated which type of infrastructure leads to the best network design as well as the degree of savings and service improvements that can be expected from the architecture proposed. Results show that the number of BSs and the energy consumption in an infrastructure with four overlaying tiers can be reduced to one third and the number of served users can be increased up to 17 percent in comparison with an infrastructure with a single tier. Moreover the approximative algorithms reduced the execution time required for the definition of a radio distribution up to one tenth of that required by the ILP formulation. Finally, results show that an infrastructure with two tiers of RAUs yields the best trade-off between computational cost and quality of results for the optimization objectives considered.

This paper is organized as follows. Section 2 introduces the proposed architecture. Section 3 presents an ILP formulation for the problem. Section 4 shows the algorithms based on linear relaxation techniques for fast

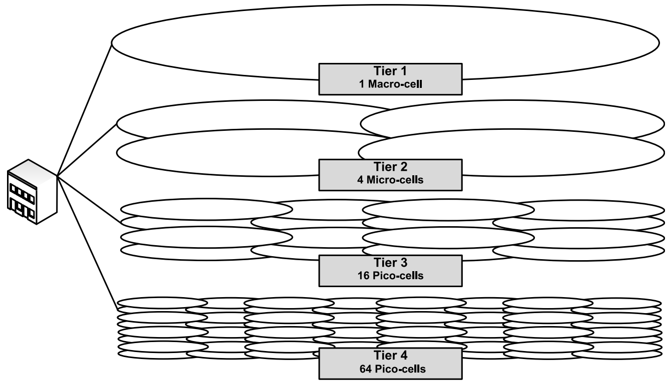


Fig. 2. Multi-tier structure of cells used by optimizer.

solutions. Section 5 presents numerical results. Section 6 presents related work, and, finally, Section 7 concludes the paper.

2 Proposed Architecture

The architecture proposed here consists of radio resources (BSs) located at management sites (BSCs), which are dynamically distributed to a large number of remote antennas units (RAUs), to cope with the varying number of mobile users. Fig. 1 shows an example of a network scenario, with one BSC and several RAUs, in which one macro-cell, three micro-cells and one pico-cell were deployed to provide coverage to all mobile stations (MSs).

In this architecture, the RAUs are organized in a hierarchical structure making possible the deployment of cells with different radii in a multi-tier fashion (Fig. 2). Deploying static cells with a fixed size would lead to resource waste, since user density in the network varies and congestion can ”migrate” from one region to another in the network. One solution to cope with this variability is to implement cells with different sizes, so that all users can be covered with minimum costs, reducing cell sizes only when necessary. An algorithm at the BSC can indicate the splitting and merging of cells to optimize this arrangement and sizes. The splitting of large cells into smaller ones increases network capacity and also the costs. Merging, however, unites small and contiguous cells into a single larger one, thus decreasing the network capacity but also the number of required BS.

In multi-tier architecture, a cluster of small cells (in tier N) can be obtained by splitting a large cell in tier $N-1$, whereas a cell in tier N can be obtained by merging cells in tier $N+1$ (Fig. 2).

3 Problem Modeling Using Integer Linear Programming

The proposed optimization model suggests the deployment of small-coverage cells in congested areas and large-radius cells in low-density areas, so that the number of BSs used can be minimized. It associates network resources (centralized at the BSCs) to the RAUs to provide a dynamic configuration of network topology in order to cope with user mobility. It is assumed that the RAUs can be dynamically "turned on" and "off", creating new cells when needed or merging them when they are no longer necessary.

The solution of the optimization problem determines: i) the BSCs that should operate in the network; ii) the BSs that should be activated by the operating BSCs; iii) the RAUs associated with the active BSs; and iv) the MSs served by the associated RAUs.

An ILP model formulates the problem with the following notation:

$\mathcal{C} = \{C_1, C_2, \ldots, C_p\}$: set of BSCs;
$\mathcal{B} = \{B_1, B_2, \ldots, B_o\}$: set of BSs;
$\mathcal{R} = \{R_1, R_2, \ldots, R_m\}$: set of RAUs;
$\mathcal{M} = \{M_1, M_2, \ldots, M_n\}$: set of MSs;
v : minimum percentage of served MSs;
t : number of tiers of RAUs;
$\mathcal{U}_i$: sets of RAUs in the tier i, $i \leq t$;
q : number of RAUs per cluster;
$a_{i,j}$: 1 if BS B_i is located at the BSC C_j; otherwise 0;
c_i : capacity of BS B_i;
$b_{i,j}$: 1 if RAU R_i is connected to BSC C_j through fiber-optic; otherwise 0;
r_i : coverage radius of RAU R_i;
$P_{R_i} = (X_{R_i}, Y_{R_i})$: geographical location of RAU R_i;
d_i : demand of MS M_i;
$P_{M_i} = (X_{M_i}, Y_{M_i})$: geographical location of MS M_i;
w_i : class type of MS M_i;
$dist_{i,j} = \sqrt{(X_{M_i} - X_{R_j})^2 + (Y_{M_i} - Y_{R_j})^2}$: distance between MS M_i and RAU R_j.

The decision variables are:

$x_{i,j,k}$: 1 if the RAU R_i is associated with the BS B_j, located at the BSC C_k; otherwise 0;
$y_{i,j}$: 1 if the MS M_i is served by the RAU R_j; otherwise 0.

The constraints of the problem are the following:

$$x_{i,j,k} \in \{0,1\} \quad \forall i \in \mathcal{R}, \forall j \in \mathcal{B}, \forall k \in \mathcal{C}, \tag{C1}$$
$$y_{i,j} \in \{0,1\} \quad \forall i \in \mathcal{M}, \forall j \in \mathcal{R}, \tag{C2}$$
$$x_{i,j,k} \leq b_{i,k} \quad \forall i \in \mathcal{R}, \forall j \in \mathcal{B}, \forall k \in \mathcal{C}, \tag{C3}$$
$$x_{i,j,k} \leq a_{j,k} \quad \forall i \in \mathcal{R}, \forall j \in \mathcal{B}, \forall k \in \mathcal{C}, \tag{C4}$$
$$\sum_{j \in \mathcal{B}} \sum_{k \in \mathcal{C}} x_{i,j,k} \leq 1 \quad \forall i \in \mathcal{R}, \tag{C5}$$
$$\sum_{i \in \mathcal{R}} \sum_{k \in \mathcal{C}} x_{i,j,k} \leq 1 \quad \forall j \in \mathcal{B}, \tag{C6}$$
$$\sum_{j \in \mathcal{R}} y_{i,j} \leq 1 \quad \forall i \in \mathcal{M}, \tag{C7}$$
$$\sum_{i \in \mathcal{M}} \sum_{j \in \mathcal{R}} y_{i,j} \geq n.v, \tag{C8}$$
$$\sum_{l \in \mathcal{B}} \sum_{k \in \mathcal{C}} x_{j,l,k} \geq y_{i,j} \quad \forall i \in \mathcal{M}, \forall j \in \mathcal{R}, \tag{C9}$$
$$y_{i,j}.dist_{i,j} \leq r_j \quad \forall i \in \mathcal{M}, \forall j \in \mathcal{R}, \tag{C10}$$
$$\sum_{i \in \mathcal{M}} y_{i,j}.d_i \leq \sum_{l \in \mathcal{B}} \sum_{k \in \mathcal{C}} x_{j,l,k}.c_l \quad \forall j \in \mathcal{R}, \tag{C11}$$
$$\sum_{f \in \mathcal{R}} \sum_{g \in \mathcal{C}} (x_{k,f,g} + x_{\mathcal{U}_{\lfloor k/q^{j-i} \rfloor},f,g}) \leq 1, \quad \forall i,j \in N^+ | i < t, i+1 < j \leq t, \forall k \in \mathcal{U}_i. \tag{C12}$$

Constraints $C1$ and $C2$ establish all decision variables as binary. Constraint $C3$ ensures that a RAU can only be associated with a BS of a certain BSC if there is an optical fiber link connecting the RAU to the BSC. Constraint $C4$ ensures that a RAU can only be associated with a BS of a BSC if the BS belongs to that BSC. Constraints $C5$ and $C6$ establish a one-to-one association between the RAUs and the BSs. Constraint $C7$ ensures that each MS will be served by only one RAU. Constraint $C8$ guarantees that a minimum percentage of MSs will be covered, which imposes a bound to network cost reduction. Constraint $C9$ establishes that only RAUs which are associated with a BS can provide coverage to users. Constraint $C10$ enforces that RAUs can only serve users in their coverage area. Constraint $C11$ limits the aggregated demand that a cell can handle out will be less than or equal to the BS capacity, thus assuring minimum quality of service. Finally, constraint $C12$ prevents the overlapping of coverage of the RAUs from different tiers.

These constraints give rise to different formulations with four different objective functions. Each objective function targets certain aspects of network operation.

The first objective function minimizes the number of BSs used, as this will reduce network costs. In this formulation, it is not guaranteed the coverage for all MSs, but it is assured for at least the minimum required percentage. *Objective Function* 1 is

$$Minimize \sum_{i \in \mathcal{R}} \sum_{j \in \mathcal{B}} \sum_{k \in \mathcal{C}} x_{i,j,k}. \tag{1}$$

The second objective function maximizes the number of MSs served, prioritizing those belonging to the higher classes (w), thus, yielding maximization of revenue. *Objective Function 2* is

$$Maximize \sum_{i \in \mathcal{M}} \sum_{j \in \mathcal{R}} y_{i,j}.w_i. \tag{2}$$

The third objective function tries to achieve the two criteria defined above, simultaneously. It is composed of two separate objectives

$$f_1 = Minimize \sum_{i \in \mathcal{R}} \sum_{j \in \mathcal{B}} \sum_{k \in \mathcal{C}} x_{i,j,k}$$
$$f_2 = Minimize \sum_{i \in \mathcal{M}} w_i - \sum_{i \in \mathcal{M}} \sum_{j \in \mathcal{R}} y_{i,j}.w_i.$$

The objective function f_1 minimizes the number of BSs used, while f_2 minimizes the revenue loss. In f_2, $\sum_{i \in \mathcal{M}} w_i$ gives the maximum network revenue and the second sum, the revenue resulting from the coverage of users; the difference between these two provides revenue loss. Instead of maximizing the revenue, its loss is minimized so that f_1 and f_2 can both be stated as minimization expressions. This avoids a formulation involving minimization and the maximization of different metrics, thus facilitating the ILP formulation.

The third objective function aims at minimizing both the number of BSs used (f_1) and revenue loss (f_2). These two objective are conflicting, since the minimization of one leads to the maximization of the other; such a conflict is common in multi-objective optimization problems (MOPs), since an optimal solution is not unique as is in mono-objective problems, and the solution is given as a set of values [10].

There are several ways of solving multi-objective optimization problems. Heuristics generally give good approximations but depend on prior knowledge of the problem and can at times provide solutions far from the optimal. Another way of solving a MOP, especially when dealing with problems not yet well investigated, such as resource allocation in RoF, would be by aggregating all objective functions, to create a single aggregated objective function (AOF). One common AOF is the linear weighted sum of the objective functions: $F(f_1, f_2, \ldots, f_n) = \alpha \times f_1 + \ \beta \times f_2 + \cdots + \gamma \times f_n$, with the sum of all weights (α, β, γ) equal to 1.

The technique used for the third objective function aggregates the objective functions f_1 and f_2, as below:

$$F(f_1, f_2) = \alpha f_1 + (1-\alpha) f_2 = \alpha \left(\sum_{i\in\mathcal{R}} \sum_{j\in\mathcal{B}} \sum_{k\in\mathcal{C}} x_{i,j,k} \right) + (1-\alpha) \left(\sum_{i\in\mathcal{M}} w_i - \sum_{i\in\mathcal{M}} \sum_{j\in\mathcal{R}} y_{i,j}.w_i \right)$$

where, $0 \leq \alpha \leq 1$.

Objective Function 3 is then denoted by

$$Minimize \quad F(f_1, f_2). \tag{3}$$

The fourth objective function minimizes the network power consumption. To assess this consumption, the power consumption of all components is considered and some simplifying assumptions made. The total network power consumption is defined as

$$P = N_{BSCs}.C_{BSC} + N_{BSs}.C_{BS} + N_{RAUs}.C_{RAU} + C_{optical},$$

where, $N_{BSCs}, N_{BSs}, N_{RAUs}$ are, respectively, the number of operating BSCs, BSs and RAUs; C_{BSC}, C_{BS}, C_{RAU} are, respectively, the power consumption of one BSC, one BS and one RAU; and $C_{optical}$ is the power consumption of the optical infrastructure.

The consumption of the BSCs usually includes provisioning of power to the building, due to building power as well as air conditioning and maintenance of the main site equipment. The consumption of the BSs results from modulating/coding and all digital processing of the network. The consumption of the RAUs is due to optics/RF conversion, power amplification and RF propagation. The latter represents the major power consumption of the network. Finally, power consumption of the optical infrastructure is basically the consumption of active fiber optic equipment and it usually negligible.

The main portion of the network power consumption is located at the RAUs, and it can be split into two distinct parts:

$$C_{RAU} = C_{optical/RF} + C_{RF},$$

where $C_{optical/RF}$ is the consumption due to optical/RF conversion. This is fixed at all operating RAUs and negligible when compared to the consumption due to power amplification and RF irradiation (C_{RF}). The C_{RF} depends on the distance between the RAUs and the MSs; it can be formulated by using the log-distance path loss model and antennas with unitary gain, as

$$C_{RF} = \frac{1}{\epsilon}.K_{PL}.P_{thr}.\left(\frac{d}{d_0}\right)^{\alpha},$$

where ϵ is the power amplifier efficiency, K_{PL} the free space path loss at d_0, P_{thr} the power threshold at the receiver and, d the distance between the RAU and the MS.

It can be seen that the total power consumption of the network is proportional to the number of active cells as well as to the distance between RAUs and MSs since the RF power consumption increases to the α-power of the distance. However, a large number of small cells increase the consumption of network elements such as BSCs and BSs.

The optimization model used in this paper employs the *Objective Function 4*, denoted by

$$Minimize \sum_{i\in\mathcal{R}} \sum_{j\in\mathcal{B}} \sum_{k\in\mathcal{C}} x_{i,j,k}.(C_{BS} + C_{optic/RF}) + \sum_{i\in\mathcal{M}} \sum_{j\in\mathcal{R}} y_{i,j} \left(\frac{1}{\epsilon}.K_{PL}.P_{thr}.\left(\frac{dist_{i,l}}{d_0} \right)^{\alpha} \right). \tag{4}$$

In the proposed architecture the number of BSs (N_{BSs}) is equal to the number of RAUs (N_{RAUs}), so for each involved cell (first summation of *Objective Function 4*) we need to take into account the values C_{BS} and $C_{optic/RF}$. For each user served (second summation of *Objective Function 4*), it is necessary to sum up the RF power consumption (C_{RF}). It is assumed that the C_{BSC} and $C_{optical}$ are negligible when compared to the consumption of other network elements. The actual values of C_{BS}, $C_{optic/RF}$ and ϵ depend on the tier of the deployed cell. Cells with large radii consume more energy and power amplifier inefficiency represents a significant amount of energy wasted. It is assumed that users are active all the time.

4 Approximative Algorithms Based on Linear Relaxation Technique

The problem of allocation of radio resource in RoF is an extension of the classical problem of base station positioning; it is, therefore, an NP-hard problem [11] and optimal solutions in real time are only feasible for small instances of the problem. Large instances require either heuristics or approximative algorithms.

Although the integer linear programming formulation yields an optimal solution, the time required to produce it may not be feasible for mobile networks. To circumvent this restriction, we have proposed algorithms that employ a linear relaxation technique to find quasi-optimal solutions in short periods. Linear relaxation consists of obtaining partial fractional solutions with the rounding off of real values to integers. Relaxation-based solutions can be considered to be probability values and, by using iterative randomized rounding techniques, the probability values can be rounded off to integer values that satisfy the original constraints. Relaxation algorithms replaced constraints $C1$ and $C2$ with $C1'$ and $C2'$, making the values of the decision variables real values, instead of integers

$$x_{i,j,k} \in [0,1] \qquad \forall i \in \mathcal{R}, \forall j \in \mathcal{B}, \forall k \in \mathcal{C} \qquad (\text{C1}')$$
$$y_{i,j} \in [0,1] \qquad \forall i \in \mathcal{M}, \forall j \in \mathcal{R}. \qquad (\text{C2}')$$

Changing the numerical type of decision variables values makes possible to consider them as probabilities and develop probabilistic algorithms based on rounded offs values and approximations.

In this paper, three different algorithms based on linear relaxation have been proposed. All algorithms receive as input a solution given by a linear programming formulation. During the approximation process other linear programming problems can be executed; with each execution having previous approximate solutions as input. Indeed, the final solution is obtained by solving successive linear programming problems that progressively approximate solutions to solutions having integer values. The efficiency of these algorithms arises from the fact that the time required for solving linear programming problems is much shorter than that required to solve large integer linear programming problems for large instances.

Algorithm 1 minimizes the number of BSs used. Algorithm 2 maximizes the revenue, and Algorithm 3 tries to achieve both objectives. All three algorithms receive as input a solution derived from a linear optimization problem and a threshold probability value ($Prob_{thr}$). The initial solution with real values is used to start the rounding off process and the threshold probability value is used for decisions about associating MSs to RAUs. This threshold value should be previously estimated using empirical methods, which takes into consideration the load and dynamics of the network. Small values of $Prob_{thr}$ lead to results far from optimal, but are more likely to ensure feasible solutions; high values of $Prob_{thr}$ can result in better optimized results, but increase the odds of making a problem infeasible.

Algorithm 1 is divided into two steps. In the first step, the value of the decision variables that establish the network infrastructure are rounded off and, then, in the second step, the values of the decision variables that determine the association between MSs and RAUs are also rounded off. In Lines 1 to 19, the algorithm decides on the associations between RAUs and BSs. From the highest to the lowest tier (Line 1), a uniform random variable $U[0,1]$ value is selected for each RAU and these values are used for decisions on associating the RAU with a BS (Line 4). If the highest real value found by the optimizer for a RAU (Line 3) is greater or equal to the randomly drawn value, then this RAU is associated with the BS; otherwise it is not. In case of association, a new constraint is added to the formulation, and another execution is performed (Line 6); this new constraint sets as 1 the value of the decision variable of the just associated RAU. If the chosen RAU is not associated, the decision variable is set as 0. In such cases, the linear problem is executed again (Line 12). In an attempt to circumvent potential misleading decisions, the algorithm checks whether a new linear problem has become infeasible after the addition of the new constraint. If it does become infeasible, the last added constraint is removed and a new constraint is added, with this new constraint making the opposite decision about rounding, so that if the previous constraint would have associated the RAU with the BS, the new constraint will remove that association (Lines 7 to 10); if the previous constraint would not have associated the RAU with the BS the new constraint guarantees the association (Lines 13 to 16). After executing this process to all RAUs and the new constraints defining the associations between RAUs and BSs are added, the network infrastructure has been defined.

Algorithm 1 Linear relaxation for minimizing the number of BSs used

Require: L: linear programming solution.
$Prob_{thr}$: threshold probability for choosing MSs.
Ensure: I: integer linear programming solution
1: **for** each tier l in decreasing order of radius **do**
2: **for** each RAU r of tier l in random order **do**
3: Find the highest probability $x_{r,j,k}$, $\forall j \in \mathcal{B}$ and $\forall k \in \mathcal{C}$
4: Draw a uniform random variable between $[0,1]$
5: **if** highest probability $(x_{r,j,k}) \geq$ drawn value **then**
6: Add constraint $x_{r,j,k} = 1$ and re-run the linear programming formulation
7: **if** new problem is infeasible **then**
8: Remove constraint $x_{r,j,k} = 1$
9: Add constraint $\sum_{\forall p \in \mathcal{C}} \sum_{\forall o \in \mathcal{B}} x_{r,o,p} = 0$
10: **end if**
11: **else**
12: Add constraint $\sum_{\forall p \in \mathcal{C}} \sum_{\forall o \in \mathcal{B}} x_{r,o,p} = 0$ and re-run the linear programming formulation
13: **if** new problem is infeasible **then**
14: Remove constraint $\sum_{\forall p \in \mathcal{C}} \sum_{\forall o \in \mathcal{B}} x_{r,o,p} = 0$
15: Add constraint $x_{r,j,k} = 1$
16: **end if**
17: **end if**
18: **end for**
19: **end for**
20: $sum_y \leftarrow$ Amount of MSs already served by the linear programming formulation
21: **for** $i \leftarrow 0$; $(sum_y < v.n)$ and $(i < n)$; $i++$ **do**
22: **if** MS i has not yet been served **then**
23: Randomly find an RAU j such that $y_{i,j} \geq Prob_{thr}$
24: **if** exists such RAU j **then**
25: Calculate the aggregated demand of all MSs already served by RAU j
26: **if** capacity of the BS associated with RAU j supports the aggregated demand plus d_i **then**
27: Add constraint $y_{i,j} = 1$
28: $sum_y \leftarrow sum_y + 1$
29: **else**
30: Add constraint $\sum_{\forall l \in \mathcal{R}} y_{i,l} = 0$
31: **end if**
32: **else**
33: Add constraint $\sum_{\forall l \in \mathcal{R}} y_{i,l} = 0$
34: **end if**
35: **end if**
36: **end for**
37: **while** $i < n$ **do**
38: Add constraint $\sum_{\forall l \in \mathcal{R}} y_{i,l} = 0$
39: $i \leftarrow i + 1$
40: **end while**
41: Re-run the linear programming formulation

The second step of Algorithm 1 (Lines 20 to 41) finalizes the rounding off of the values of the y variables. For all MSs that have not yet been associated with RAUs (Line 22), the algorithm finds a RAU with which the MS is most likely to be associated (Line 23). If the algorithm finds such RAU it tries to associate the MS with it, while considering both the required MS demand and the RAU capacity. If the association attempt is successful, a new constraint is added (Line 27) to establish this association; otherwise the MS will not be served by any RAU (Lines 30 and 33). Association attempts are performed until either all MSs are verified or the minimum percentage of served MSs has been reached (Line 21). Since new constraints are added in the second part of the algorithm, the problem must be executed again in order to find the final solution.

Algorithm 2 Linear relaxation for maximizing operator revenue

Require: L: linear programming solution.
$Prob_{thr}$: threshold probability for choosing MSs.
Ensure: I: integer linear programming solution
1: Define M' as a list of all MSs in decreasing order of revenue
2: Defines R' as a empty set {This set will store the RAUs already associated}
3: **for** each MS i in list M' **do**
4: Randomly find a probability $y_{i,j}, \forall j \in \mathcal{R}$ such that $y_{i,j} \geq Prob_{thr}$
5: **if** probability $y_{i,j}$ was found **then**
6: **if** RAU j is already in set R' **then**
7: Calculate the aggregated demand of all MSs already served by RAU j
8: **if** capacity of the BS associated with RAU j supports the aggregated demand plus d_i **then**
9: Add constraint $y_{i,j} = 1$
10: **else**
11: Add constraint $\sum_{j\in\mathcal{R}} y_{i,j} = 0$
12: **end if**
13: **else**
14: Find the highest probability $x_{j,k,l}$, $\forall k \in \mathcal{B}$ and $\forall l \in \mathcal{C}$
15: **if** capacity c_k supports d_i **then**
16: Add constraint $x_{j,k,l} = 1$
17: Add constraint $y_{i,j} = 1$
18: Re-run the linear programming formulation
19: **if** new problem is infeasible **then**
20: Remove constraint $x_{j,k,l} = 1$
21: Remove constraint $y_{i,j} = 1$
22: Add constraint $\sum_{j\in\mathcal{R}} y_{i,j} = 0$
23: **else**
24: Add RAU j to set R'
25: **end if**
26: **end if**
27: **end if**
28: **else**
29: Add constraint $\sum_{j\in\mathcal{R}} y_{i,j} = 0$
30: **end if**
31: **end for**
32: **for** all RAU i not included in set R' **do**
33: Add constraint $\sum_{\forall p\in\mathcal{C}} \sum_{\forall o\in\mathcal{B}} x_{i,o,p} = 0$
34: **end for**
35: Re-run the linear programming formulation

Algorithm 2 is composed of three steps. The first step (Lines 1 and 2) corresponds to the initialization of the auxiliary data structures M' and R'. List M' has all MSs, ordered by decreasing the revenue value. The set R' is initially empty and stores the RAUs chosen in the final solution. The second step involves Lines 3 to 31; it rounds off the values of decision variables related to the association between MSs and RAUs. The algorithm tries to associate each MS with RAUs in the list M', by seeking probability values greater than or equal to the $Prob_{thr}$ (Line 4). If this probability value exists, and the RAU is already in set R', the algorithm calculates the aggregated demand of all MSs already served by this RAU (Line 7), and, if this RAU can support the demand of the MS under consideration, the algorithm associates that MS with the RAU. If the RAU is not in the set R', the algorithm verifies if the demand of that MS could be supported by the BS which is the most likely to be associated with this RAU (Lines 14 and 15). If the demand can be supported, the constraints that link the RAU to the BS chosen and that establish that the MS will be served by this RAU are added, and another execution is run (Lines 16 to 18). A new execution of the linear problem is only run when new RAUs are added to set R'. If the new problem is infeasible, the algorithm modifies the last constraints added (Lines 19 to 23) so that an attempt can be made to avoid infeasibility with new network infrastructure. At the end of second step, all MSs have been analyzed and all variables y have integer values. In the third step, all the variables x corresponding to RAUs not associated with any BSs by the algorithm receive a null value (Line 33). At the end, a new linear problem is executed, to ensure that all variables x have integer values.

Algorithm 3 Linear relaxation for minimizing the number of BSs used and revenue loss

Require: L: linear programming solution.
$Prob_{thr}$: threshold probability for choosing MSs.
Ensure: I: integer linear programming solution
1: Define M' as a list of all MSs in decreasing order of revenue
2: **for** each tier l in decreasing order of radius **do**
3: **for** each RAU r of tier l in random order **do**
4: Draw a uniform random variable between $[0, 1]$
5: Find the highest probability $x_{r,j,k}$, $\forall j \in \mathcal{B}$ and $\forall k \in \mathcal{C}$
6: **if** highest probability $(x_{r,j,k}) \geq$ drawn value **then**
7: Add constraint $x_{r,j,k} = 1$ and re-run the linear programming formulation
8: **if** new problem is infeasible **then**
9: Remove constraint $x_{r,j,k} = 1$
10: Add constraint $\sum_{\forall p\in\mathcal{C}} \sum_{\forall o\in\mathcal{B}} x_{r,o,p} = 0$
11: **end if**
12: **else**
13: Add constraint $\sum_{\forall p\in\mathcal{C}} \sum_{\forall o\in\mathcal{B}} x_{r,o,p} = 0$ and re-run the linear programming formulation
14: **if** new problem is infeasible **then**
15: Remove constraint $\sum_{\forall p\in\mathcal{C}} \sum_{\forall o\in\mathcal{B}} x_{r,o,p} = 0$
16: Add constraint $x_{r,j,k} = 1$
17: **end if**
18: **end if**
19: **if** a new RAU was associated in the current iteration **then**
20: **for** all MS in list M' **do**
21: Find the highest probability $y_{i,j}$ $\forall j \in \mathcal{R}$
22: **if** highest probability $(y_{i,j}) \geq Prob_{thr}$ **then**
23: Add constraint $y_{i,j} = 1$
24: Remove MS i from list M'
25: **end if**
26: **end for**
27: **end if**
28: **end for**
29: **end for**
30: Re-run the linear programming formulation

In Algorithm 3, the first line corresponds to the initialization of the auxiliary data structure M', which stores all MSs in decreasing order of value of revenue (w). Started with the highest tier (Line 2), the RAUs for each tier are chosen randomly (Line 3). A uniform random variable $U[0, 1]$ is selected for each RAU (Line 4) which is used to decide on the association of a RAU with the BS with the highest real probability value (Line 5). If the highest solution value for the chosen RAU (Line 6) found by the optimizer is greater than or equal to the value drawn, then the chosen RAU will be associated with the BS; otherwise it is not. If the chosen RAU is associated, a new constraint is added and the linear programming formulation is re-executed (Line 7). A different constraint is added if the association of the chosen RAU is rejected and the program is again re-executed (Line 13). As an attempt to circumvent potentially misleading decisions, the algorithm checks whether the new linear problem

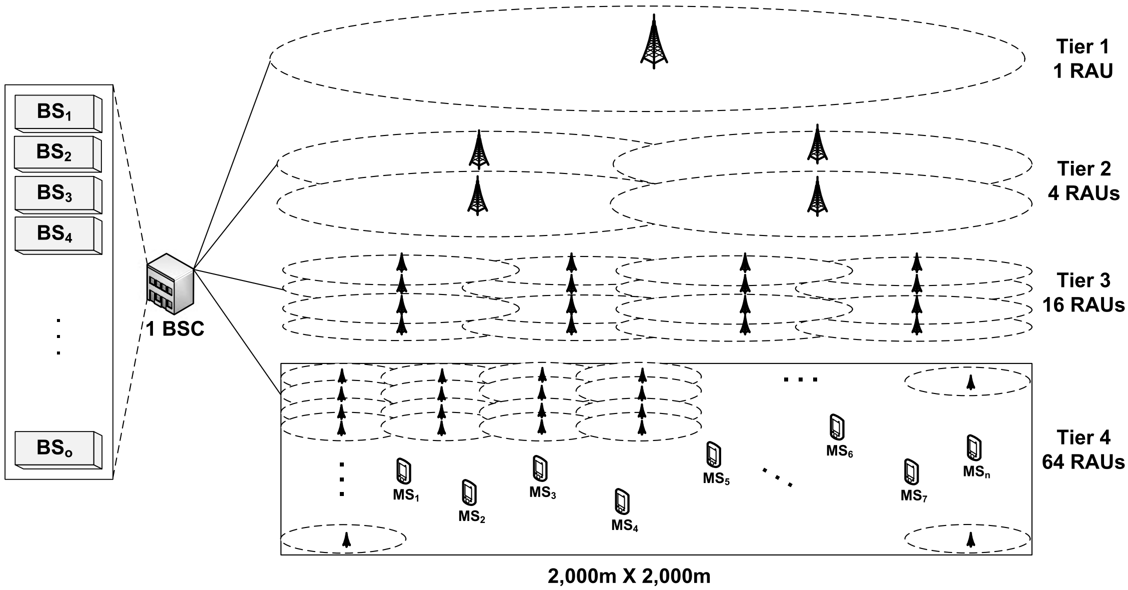


Fig. 3. Radio-over-Fiber infrastructure used in the evaluation.

becomes infeasible after the addition of the last constraint. If a constraint imposing the association of a specific RAU with a specific BS makes the problem infeasible, the constraint is removed and another constraint is added stating that this RAU should not be associated with any BS (Lines 8-10 and Lines 22-25). If during the iteration a new RAU is chosen for association (Line 19) and the program is re-executed, the algorithm seeks in the ordered list M' and attempt to find the highest probability value for each MS; if this probability is greater than or equal to Pr_{thr}, then a new constraint (Line 23) is added to the problem, associating the MS to the chosen RAU. All MSs served are finally removed from the list M' (Line 24).

5 Numerical Evaluation

The RoF network infrastructure used in the numerical evaluation consists of a single BSC and several RAUs distributed uniformly in an area of 2 Km $\times$ 2 Km. The RAUs are organized in a multi-tier fashion in four tiers with the three lowers consisting of clusters of cells. The highest tier covers a cell with a radius of 1420 m; the second tier consists of 4 RAUs with radius of 710 m, disposed in a 2×2 grid; the third tier contains 16 RAUs with radii of 360 m each, and the lowest tier, 64 RAUs with radii of 180 m each. The RAUs of two different tiers cannot operate simultaneously for the coverage of a given area. In the worst case, the network will operate with 64 BSs, which is the case if all RAUs from the lowest tier are active.

In the experiments, the network infrastructure was changed in order to evaluate the results for different configurations. The network infrastructure, thus, consisted of 1 BSC, 85 RAUs, up to 64 BSs, each with a capacity of 30 MSs, and up to 1000 MSs. For each experiment, a different number of BSs and MSs were considered. All the BSs can be associated with any of the 85 RAUs, since they are all connected by optical fiber links. Fig. 3 illustrates the infrastructure.

The optimization model was implemented using the C programming language and the optimization library FICO Xpress 7.0 [12], which implements the LP-based Branch and Bound technique for solving ILP problems. All experiments consisted of simulations and were executed in a workstation with an Intel Core 2 Quadcore processor at 2.6 GHz, 3 GB of RAM and a Debian GNU/Linux kernel 2.6.23.1 operating system. The Random Trip Model [13] was employed using the urban scenario of the streets in Houston, Texas, USA, near West University. The mobility model was used jointly with the Network Simulator 2 [14] in order to simulate the movement and position of the mobile stations. For each simulation, at least 10 snapshots of the position of the MSs were taken to compute the desired statistics and intervals with a 95 percent confidence level were derived. Confidence intervals smaller than 5 percent were omitted in the graphs in order to improve visualization of the results.

In the simulations, four different network infrastructures were considered: *Infrastructure A* involved only the lowest tier of RAUs (64 RAUs); *Infrastructure B* consisted of the lowest 2 tiers ($64 + 16$ RAUs); *Infrastructure C* was composed by three tiers ($64 + 16 + 4$ RAUs); and *Infrastructure D* involved all four tiers ($64 + 16 + 4 + 1$ RAUs). By considering these four infrastructures, it is possible to evaluate the benefits of structuring the RAUs in different hierarchical networks. The flexibility for reducing the number of RAUs increases with the number of tiers in the infrastructure, but the optimization problem demands more computational effort.

All experiments involved one of the four previously specified objective functions and/or one of the three approximative algorithms. When employing relaxation algorithms, the input probability threshold value ($Prob_{thr}$) was set to 0.9; this value was chosen on the basis of preliminary evaluation, and it represents a threshold value for which less than 5 percent of the simulations resulted in infeasible problems.

5.1 Minimization of BSs

The first set of experiments was designed to reduce the number of BSs used to the minimum. The number of MSs

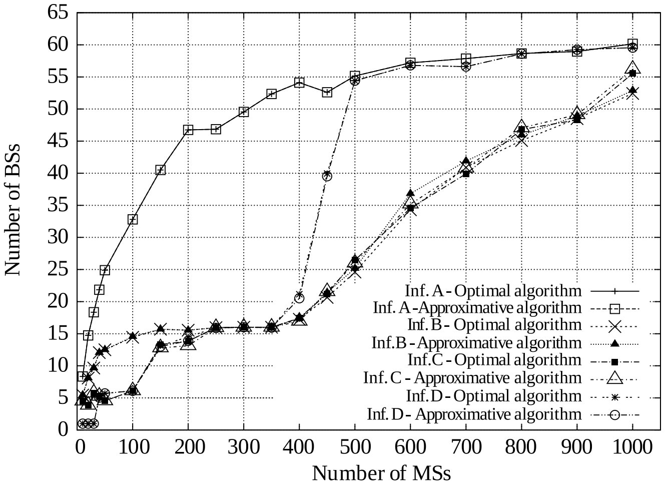


Fig. 4. Number of BSs used as a function of number of MSs—optimal solutions and approximate solutions.

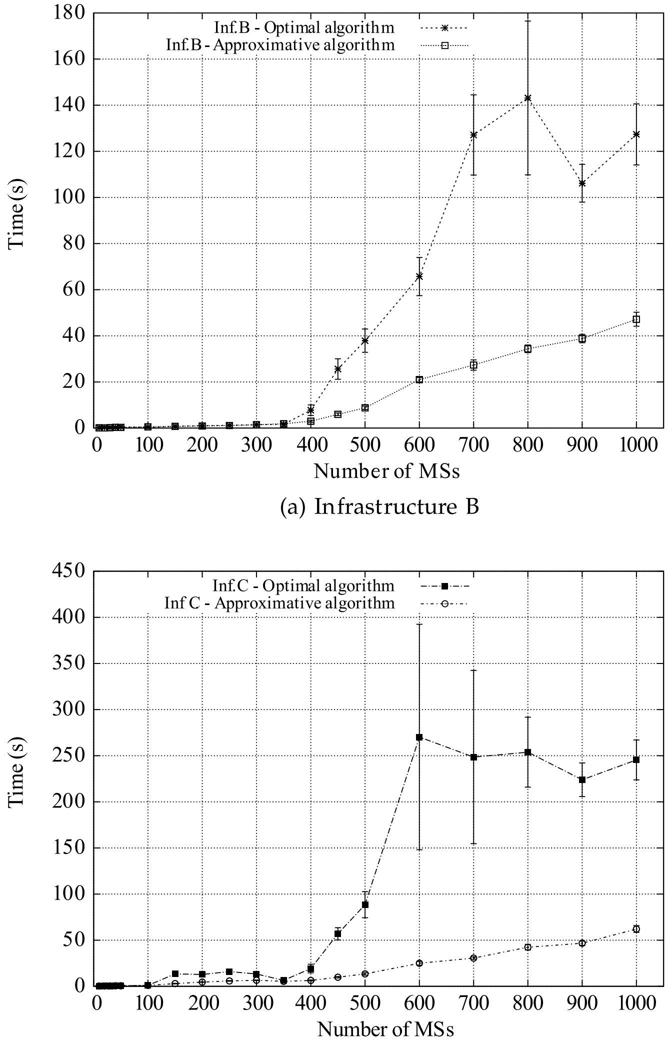
varied from 1 to 1,000 with the optimization model adjusted to serve 100 percent of the users.

Fig. 4 plots the number of BSs used for a varying number of MSs, considering all four proposed infrastructures and both integer and approximative algorithms. It can be noticed that the number of required BSs by *Infrastructure A* with just one tier of RAUs demands a much higher number of active BSs. For fewer than 100 MSs, while *Infrastructure A* with a single tier of RAUs requires more than 30 BSs, *Infrastructures C and D* require only 5 BSs. The difference between the requirements of *Infrastructure A* and that of the other infrastructures was, on average, 35 BSs, for networks with less than 400 MSs.

In the experiments, a bound of 600 s of execution time was set for the optimal algorithm. Such a limit leads to solutions for *Infrastructure D* far from the optimal since the computational demands for solving the problem with four tiers are much greater than those required to solve problems with fewer tiers. For this reason, the curve of *Infrastructure D* shows worst results than do the curves of *Infrastructure B* and *C*, when the opposite was expected.

As can be seen in Fig. 4, the results for the two types of algorithms (ILP and approximative) are very similar. For more than 400 MSs, *Infrastructure B* and *Infrastructure C* give better results with the relaxation-based algorithm (Algorithm 1), showing good performance, since these results are very similar to those given by the ILP formulation. In summary, more than three tiers is not to be recommended, due to the high computational demands. Moreover, two tiers is sufficient to reduce the number of BSs used.

The execution time for the experiments was also analyzed. Considering *Infrastructure A*, the required execution time was very small for both algorithms. When *Infrastructures B, C and D* are employed, shorter time intervals were required when using the relaxation-based algorithm. For networks with more than 400 MSs, the time required by the ILP formulation increases drastically and surpasses 150 s for *Infrastructure B* and 250 s for both *Infrastructure C* and *Infrastructure D*. Fig. 5 shows the execution time for *Infrastructures B* and *C*, which are the infrastructure types



(a) Infrastructure B

(b) Infrastructure C

Fig. 5. Duration of optimization of minimization algorithm—optimal and approximate solutions.

associated with the greatest reduction in the number of BSs used. The solution of the problem with more than 600 MSs required up to three times as long when the ILP solver was used, than when relaxation-based algorithms were used, for *Infrastructure B*; and four times as long, for *Infrastructure C*.

The large reduction in the execution time when using Algorithm 1 highlights the benefits of linear relaxation techniques for solving linear programming problems. *Infrastructure B* provides the best trade-off between network cost reduction and computational complexity, especially when using relaxation-based algorithms.

5.2 Maximization of Operator's Revenue

In these experiments, the model tried to serve as many users as possible, giving priority on the basis of the class of service.

Four classes of service were considered, 1 to 4. The revenue the operator receives from serving the users in each classes increases with the order of the class, with users of class 4 generating four times as much revenue as do those of class 1. The proportion of users was set to $40, 30, 20$ and 10 percent, for classes 1 to 4, respectively. The network consisted of 1000 MSs; the number of BSs varied from 1 to 64.

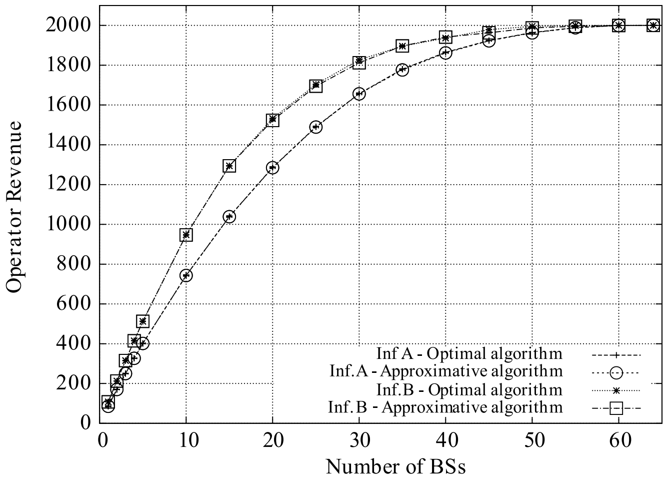


Fig. 6. Operator revenue as a function of the number of BSs—optimal and approximate solutions.

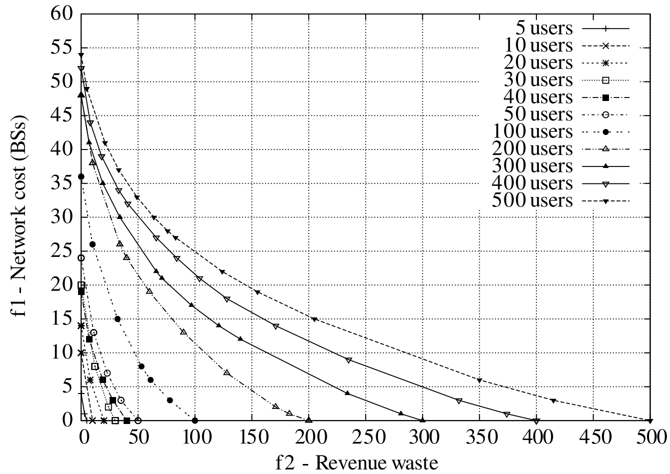


Fig. 8. Solutions of a network with up to 500 MSs, using *Infrastructure A*—optimal solutions.

Fig. 6 shows the operator revenue as a function of the number of BSs. Only the results for *Infrastructure A* and *Infrastructure B* are shown, since the results for *Infrastructure C and D* were quite similar to those of *Infrastructure B*. It is possible to see that the solutions for the ILP formulation and for the relaxation-based algorithm are very close for all experiments, which highlights the efficiency of Algorithm 2. The total revenue increases as the number of BSs increases since more MSs can be served. The maximum difference in the total revenue for *Infrastructure A and B* is slightly more than 200 (revenue units) for networks with 15 BSs. As the number of BSs increases the revenue for both infrastructures reaches a maximum value of 2,000 units, when all MSs are served.

Fig. 7 shows the time required for solving the ILP formulation and the relaxation-based algorithm for *Infrastructures A and B*. *Infrastructure A* requires only a short time for all experiments with the ILP algorithm, suggesting that it is not worth employing algorithms based on relaxation techniques for this infrastructure. The derivation of solutions using the ILP for *Infrastructures B, C and D* required a very long time, which motivated the adoption of a bound for the execution time of 300 s. When the execution time reached this bound, the ILP algorithm returns the best integer solution found, even if it is not an optimal solution. As it can be seen in Fig. 7, the time required to produce results for *Infrastructure B* is only one third long the time required by the integer algorithm with the relaxation-based algorithm when 20 to 50 BSs are involved. The same difference was seen in a comparison of results for *Infrastructures C and D*.

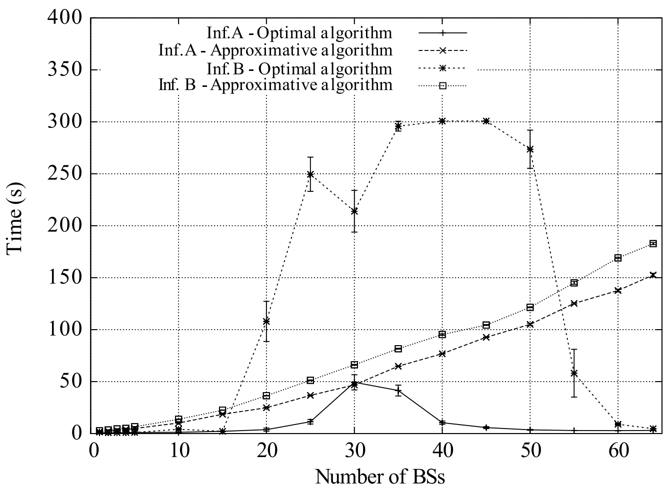


Fig. 7. Optimization duration of maximization algorithm—optimal and approximate solutions.

The results shown in Fig. 6 and the reduction in time for *Infrastructures B* (Fig. 7) show the effectiveness of Algorithm 2. *Infrastructure B* can be considered to be the one furnishing the best trade-offs between quality of results and computational requirements, especially when approximative algorithms are used.

5.3 Bi-Criteria Optimization

In these experiments, the model tries to achieve both objectives simultaneously, using *Objective Function 3*.

The weight values α of *Objective Function 3* ranged from 0 to 1 in intervals of 0.05. In the experiments the two objectives were weighted equally so that the increase of a unit in network costs had the same weight as an increase of a unit in revenue loss. It is thus essential that the variation in the value of α means the same for the two objectives; in order to achieve this, the final objective function was changed to

$$F'(f_1, f_2) = \alpha\left(\frac{f_1 - f_1^{min}}{f_1^{max} - f_1^{min}}\right) + (1-\alpha)\left(\frac{f_2 - f_2^{min}}{f_2^{max} - f_2^{min}}\right),$$

where, f_i^{min} and f_i^{max} are, respectively, the minimum and maximum values of objective function f_i.

Simulations were executed considering $F'(f_1, f_2)$ for networks with at most 500 MSs and for the four different types of infrastructures. Figs. 8 and 9 show, respectively, results for *Infrastructure A* and *Infrastructure C*. Results using *Infrastructure D* were very similar to those using *Infrastructure C*, except for networks with fewer than 30 MSs. Large values for the minimization of the function $F'(f_1, f_2)$ were obtained when employing the *Infrastructure B* or *C* for networks with more than 100 MSs; because networks with fewer than 120 MSs can be well designed with four RAUs in tier 3.

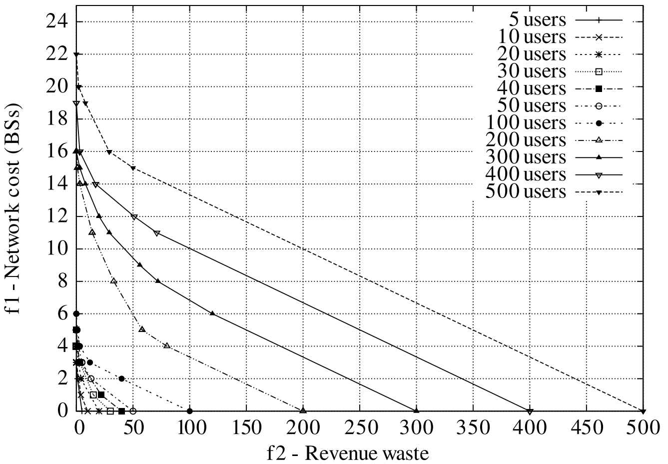


Fig. 9. Solutions for a network with up to 500 MSs, using *Infrastructure C*—optimal solutions.

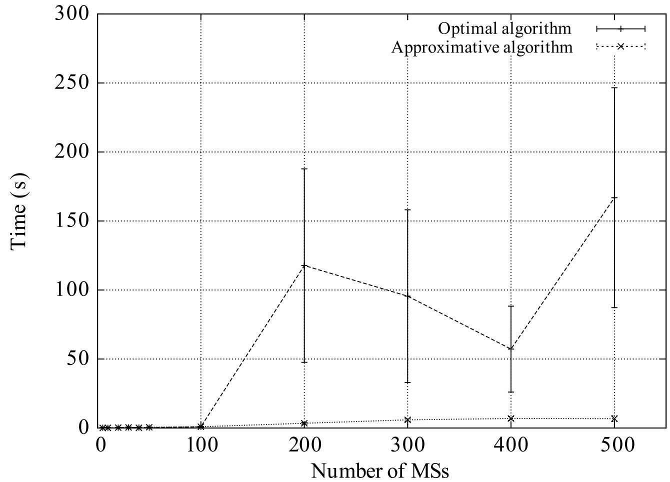


Fig. 11. Average time of processing, using *Infrastructure C.*

The network operational cost (Fig. 8) when considering *Infrastructure A* involves almost 55 RAUs for networks with 500 MSs with no revenue loss. Moreover, when using either *Infrastructure B* or *Infrastructure C*, it is possible to obtain this same revenue with only 22 BSs (Fig. 9). The same revenue at a cost reduction greater than 50 percent can thus be obtained (Fig. 8).

For networks with at most 100 MSs, a significant cost reduction can be obtained (Fig. 9). Using *Infrastructure C*, it was possible to serve all MSs (no revenue loss) with only 6 BSs, whereas with *Infrastructure B* 14 BSs were required.

The greatest network cost reduction was found when using *Infrastructure C*, but this required more computational effort to find the solutions. The time required increased proportionally to the number of MSs. With this time depending on the weighting, weight close to 0 or to 1 required less time to solve the problem, while weights between 0.3 and 0.7 required more.

Algorithm 3 produced results close to the optimal, with a significant time reduction for all types of infrastructures with the greatest reduction obtained when using *Infrastructure C* and *D*; this shows the proposed approximative technique was effective. Fig. 10 shows the approximated results given by the approximative algorithm and the optimal curves (shown in Fig. 9) for *Infrastructure C*.

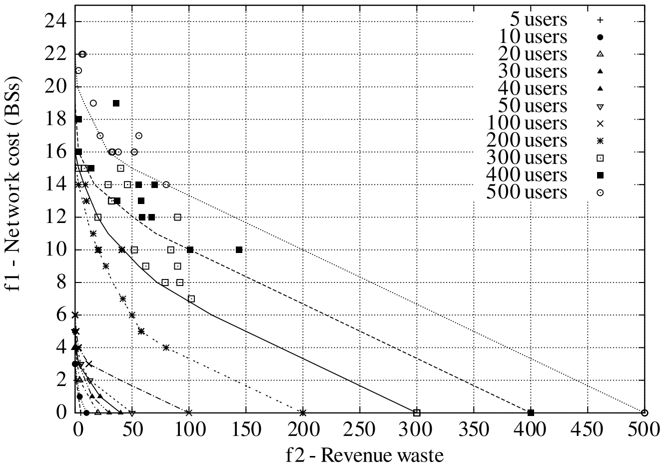


Fig. 10. Solutions of a networks with up to 500 MSs, using *Infrastructure C*—approximate solutions.

In Fig. 10, it is clear that most of the results of Algorithm 3 are very close to the optimal. For networks with up to 200 MSs, it gives results practically identical to the optimal while for those with 300, 400 and 500 users, the results are quite close.

Fig. 11 shows the mean computational time required to produce both the optimal and approximate solutions for *Infrastructure C* with various weighting. For networks with up to 100 MSs, both solutions required roughly the same time for derivation, but for networks with more than 200 MSs, a large difference in the time required is evident. The ILP algorithm required up to 25 times more time to produce results than did the relaxation-based algorithm. Moreover, the variation in the time required to produce results using the ILP algorithm is high. The computation of results with weighting values close to either 0 or to 1 was much faster than that computation with values close to 0.5. The good-quality results of approximate solutions and the greatly reduced time of processing emphasize the benefits of approximative techniques and show that the proposed optimization model can be used in applications with time constraints.

5.4 Minimization of Network Energy Consumption

The last set of experiments was designed to reduce the power consumption of the network, considering the *Objective Function 4*. The number of MSs varied from 1 to 1,000, with the optimization model adjusted to serve 100 percent of the users. The values of C_{BS}, $C_{optics/RF}$ and ϵ used in the simulations are presented in Table 1 [28]. Cells were considered: i) pico if their radii were small (tiers 3 and 4), ii) micro

TABLE 1
Parameters of Energy Consumption

	Macro cell	Micro cell	Pico cell
C_{BS}	32 W	29.5 W	3.3 W
$C_{optics/RF}$	12.9 W	6.5 W	1.0 W
ϵ	31.1%	22.8%	6.7%

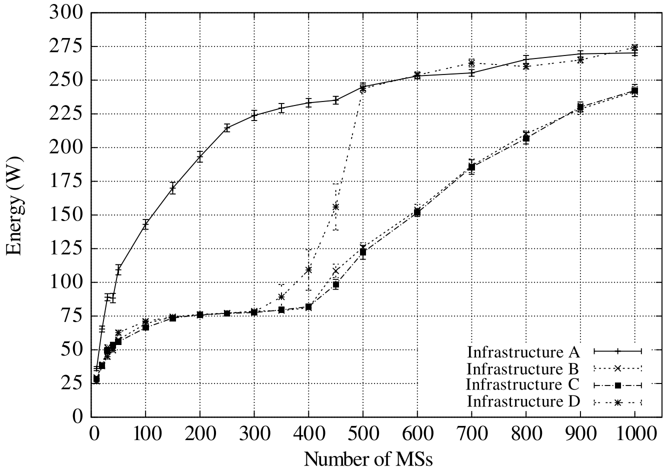


Fig. 12. Power consumption of the network.

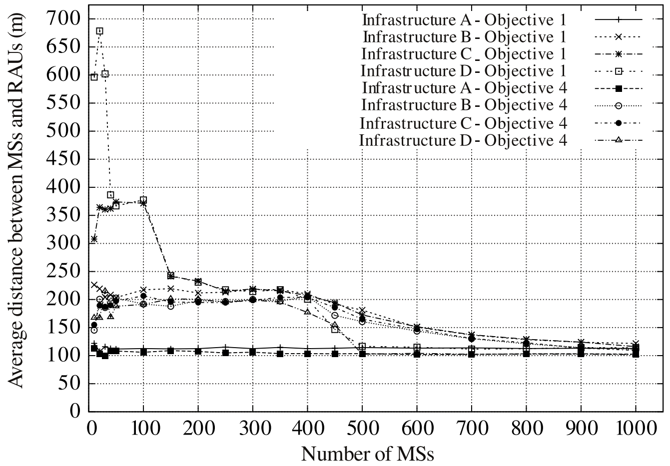


Fig. 13. Average distance between MSs and RAUs.

if they were at tier 2, and iii) macro if they have large radii (tier 1). For the calculation of C_{RF}, the following values were employed: $P_{thr} = -80$ dBm, $d_0 = 50$ m and $\alpha = 2.5$.

Fig. 12 plots the approximated total network power consumption for a varying number of MSs, considering all four infrastructures proposed. Fig. 13 plots the average distance between MSs and RAUs with the *Objective Functions 1 and 4*.

Fig. 12 shows that, except for *Infrastructure A*, is roughly the same up to 350 MSs; in these scenarios, the majority of deployed cells are on tier 3 or tier 4. In contrast to results obtained from the minimization of the number of BSs, when minimizing energy consumption, small cells are preferable due to their low energy consumption. For scenarios with more than 400 MSs, the execution time to find a solution for *Infrastructure D* reached the established upper bound (600 s), moreover, the results obtained were not optimal. The differences in power consumption between *Infrastructure A* and *Infrastructures B and C* shows that the proposed multi-tier hierarchy leads to energy-efficient operation.

Fig. 13 shows the main difference between *Objective Function 1 and 4* is that the former favors privileges large cells thus increasing the distance between MSs and RAUs, while *Objective Function 4* takes advantage of low power consumption of small cells, decreasing the distance and using more BSs. The average distance between the MSs and active RAUs is greater when *Objective Function 1* is used. In scenarios with less than 100 MSs, when employing Infrastructure D, Objective 4 can reduce the average distance to at least half of the value obtained with Objective 1. Another benefit of minimizing energy consumption is an increase in average SNR since distance between transmitters and receiver are shortened.

The results showed that *Infrastructure B* presents the best trade-off between quality of results and computational demands for *Objective Function 4*.

6 Related Work

Radio resource management (RRM) techniques applied to radio-over-fiber architecture have been the focus of recent investigations. Techniques have been extensively used in cellular network and local area network planning [15], but most of them were proposed for static decision making. One central problem for wireless network optimization is the positioning of base stations for optimal use of radio resources. Solutions for this traditional problem are usually based on static methods and can lead to resource waste in dynamic networks such as those involving mobile users. Some of the recent work on RRM in wireless networks will be briefly surveyed here.

Various RRM techniques have been proposed [16] to deal with the dynamic clustering of users in cellular network, as well as local area networks [17]. In [9], the authors argue that since system-centric RRM uses a divide-and-conquer approach and it may be potentially inefficient for mobile networks. They thus propose a user-centric approach that associates network resources with users before locating them in the coverage area. In [8], power control and base station assignment are based on the maximization of user network utility and network revenue. In [17], dynamic congestion balancing is performed by mean of the power control of APs beacon packets, increasing and decreasing the radius of cells according to the clustering of users in the local network.

RRM algorithms in the RoF scenario have not yet been thoroughly explored. In [18] and [19], the RAU positioning problem in hybrid wireless-optical networks is addressed. A greedy algorithm for solving this problem is proposed in [19], which tries to minimize the Euclidean distance between RAUs and users. In [18], a solution based on simulated annealing is proposed; the results show significant cost reduction. These solutions, however, provide last-mile access for fixed users and are not appropriate for mobile users since clustering of users is disregarded.

Although some attempts have been made to deal with the positioning problem, few have explored the cell-size adjustment, which consists of finding the best radius for each cell in order to improve spectrum or energy efficiency can be improved. The optimization of this parameter is crucial for the best network performance, since small cells can improve throughput, and resource savings, since the number of base stations required is decreased, which saves infrastructure and reduced energy costs.

In [20], a framework for cell zooming algorithms is proposed for green cellular networks. The authors compare two different algorithms, one distributed and the other centralized; results show that the second provides better results. Both algorithms, however, are based on a greedy approach and do not provide optimal results. Moreover, the implementation of cell zooming depends on features not widely deployed, such as automatic adjustment of antenna height and tilt. In [29], a two level hierarchical cellular network with dynamic cell adjustment for efficient energy operation was introduced. However, its implementation has the same problem of the cell zooming approach. Actually, cell zooming explores the concept of self-organizing networks for optimization of radio resources, dynamically defined cell sizes; these seminal papers dealing with self-organizing networks [21] for green cellular networks have shown benefit for energy savings and is currently implemented in 3GPP standard. In [21], energy waste is minimized for a multi-operator cooperative network. The final three papers mentioned show that cells, and even network elements, can be turned on and off to improve the efficiency of wireless networks. The best implementation for this approach, however, is only achieved when centralized agents are employed to make globally optimal decisions.

The solution proposed in this paper optimizes network radio resources based on a centralized architecture that can improve the efficiency of wireless networks. It presents an optimization model based on ILP and approximative algorithms for the rapid obtainment of solutions. The approximative algorithms are based on the linear relaxation of the ILP problem and employ randomized rounding; both techniques (linear relaxation and randomized rounding) have been proved to be efficient [22], [23]. However, the development of fast algorithms for RRM in centralized networks has not yet been well explored in previous work. The present paper includes a thorough study of various aspects of the problem, from modeling of the problem to the development of fast algorithms. It contains a revision of papers previously published in conference proceedings [24], [25], [26]. It differs from these last papers in that it compares four different criteria of optimization and evaluates time gains in the processing of fast algorithms.

7 Conclusion

Ths paper introduced an architecture for mobile wireless networks based on Radio over Fiber. Moreover, it proposed a resource optimization model that involves dynamic cell splitting and merging for multi-tier RoF infrastructures of RAUs. The optimization problem can be executed with different objective functions: minimization of the number of BSs used, maximization of revenue, with the two objective functions simultaneously, reducing the network cost and the revenue loss, or minimization of the energy consumption of the network. Algorithms based on relaxation technique were also presented for rapid solutions of the problem. These approximative algorithms produced results very close to the optimal ones in all cases, but required much less computational effort.

The results obtained indicate that two tiers of RAUs provide the most effective trade-off between results and computational effort, for all three different objectives: minimization of the number of BSs, maximization of revenue and minimization of energy consumption. Each objective has its own pros and cons, which that must be weighed by network operators for the best use of resources for their intended target. The reduced computational time required by the relaxation-based algorithms showed them to be feasible for the real time optimization of radio resources in mobile networks.

Acknowledgments

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