Bi-criteria Optimization of Radio Resources for Radio-Over-Fiber Access Networks

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Abstract—This article presents a radio resource optimization model for Radio-over-Fiber (RoF) access networks. The proposed model arranges cells in a multi-tier fashion with increasing coverage radius. Considering the available structure of antennas the optimizer performs dynamic cell merging and cell splitting according to mobile users’ demands for efficiently utilizing radio resources. It is proposed an integer programming model with a bi-criteria objective function that tries to minimize the use of network resources as well as to maximize network revenue. The computational demand for obtaining integer solutions increases proportionally to the number of mobile users and also to the number of tiers of antennas. In addition to the integer solutions, an algorithm based on linear relaxation technique is presented, which implies on significant computational time reduction when solving large instances of the problem. Moreover, results are very close to those given by the integer programming formulation.

Index Terms—radio-over-fiber, radio resource management, bi-criteria optimization, mobile networks.

I. INTRODUCTION

Radio-over-Fiber (RoF) technology decreases network costs and provides flexibility for radio resource optimization in mobile wireless networks. It integrates wireless and optical technologies leveraging the best of both for the deployment of efficient access networks. RoF networks usually interconnect a large number of antennas, called Remote Antenna Units (RAUs) to a few centralized management sites (Base Station Controllers - BSC), via a fiber link backhaul [1]. Radio equipments (Base Stations - BS), located at the BSC, can be dynamically associated to the RAUs to cope with users’ demands. The optical part of the network (fiber backhaul) provides reliable and high-capacity transmissions, while the wireless part (antennas and radio equipments) facilitates mobility at low cost. Previous works have demonstrated the viability of RoF transmissions [1], [2].

Radio resource management (RRM) is a challenging task in modern beyond-3G technologies, which are supposed to offer infrastructure to mobile and bandwidth-consuming applications. These techniques are essential for effective network planning, however most of recent RRM algorithms perform static decisions and do not consider users’ positioning, which can lead to resource waste in such dynamic environment. The efficient radio resource management of centralized architectures is still an open question. One of the approaches for this problem adopts a user-centric resource allocation [3], [4] that considers users’ demands for the deployment of the best cell configuration. Such approach demands a global optimization algorithm for the search of the most efficient resources distribution.

Some issues of the resource allocation problem in RoF have already been investigated by the authors of the present paper [5]. In [5], a network architecture with multi-tier structure of antennas was first presented and integer results were obtained for different scenarios with the aim of reducing network cost. In [6], the optimization model in [5] was modified and results were derived for maximizing the revenue; in addition to that, two algorithms based on linear relaxation were proposed for fast optimization of resources. Based on previous results the present paper introduces a network optimization model with a bi-criteria objective and an algorithm based on relaxation for fast solution of the bi-criteria problem.

The results derived can be used as a guideline for optimization of resources in RoF networks. The optimal solutions represent the best compromise that can be achieved between network cost and revenue increase. The approximated algorithm can be implemented when fast solution is required (mobile networks).

The paper is organized as follows. Section II presents related works. Section III introduces the proposed architecture and the integer programming formulation of the problem. Section IV shows the algorithm based on linear relaxation technique for fast solution. Section V presents numerical results and, finally, section VI concludes the paper.

II. RELATED WORKS

In mobile wireless networks, the radio resources demand varies according to users mobility. New RRM techniques have been proposed [4], to account for the dynamic clustering of users. In [3], the authors argue that due to the fact that system-centric RRM uses a divide-and-conquer approach, it can be potentially inefficient for mobile networks. They propose a user-centric approach that associates network resources to users before locating them in the coverage area. In [7], power control and Base Station assignment are performed based on the maximization of users’ network utility and network revenue.
Actually, RRM algorithms in RoF scenario has not been thoroughly explored. In [8] and [9], the RAU positioning problem in hybrid Wireless-Optical networks is addressed. A greedy algorithm for solving this problem is proposed in [9], which tries to minimize the euclidean distance between RAUs and users. In [8], a solution based on simulated annealing is proposed; results show significant cost reduction. These solutions, however, provide last-mile access for fixed users and are not appropriate to mobile users since clustering of users is disregarded.

### III. PROPOSED ARCHITECTURE AND OPTIMIZATION MODEL

The architecture considered consists of a reduced number of radio resources (Base Stations - BS) centralized at a few management sites (Base Station Controllers - BSC). These resources can be dynamically distributed to a large number of antennas (Remote Antenna Units - RAUs) spread throughout the coverage area. The Mobile Stations (MS) demand and their locations are accounted in the determination of the optimal distribution of network resources. Figure 1 shows an example of such architecture, where there is one BSC with limited number of BSs and some RAUs spread throughout the network area. In this figure the deployment of 5 cells - 1 macro-cell, 3 micro-cells and 1 pico-cell - is sufficient to provide connectivity to all MSs. Moreover, resources could be saved, since it was not necessary to associate RAU\(_1\) and RAU\(_4\) to any radio resource, because RAU\(_5\) could deploy a cell large enough to cover all MSs at that region.

![Proposed architecture example](image)

In the considered architecture, a single wireless technology is employed and the antennas are arranged in a hierarchical structure that makes possible the deployment of cells with different radii in a multi-tier fashion (Figure 2). The algorithm in the BS performs cell splitting and cell merging in order to optimize the arrangement of cell and their sizes. Cell splitting divides large cells into smaller ones, consequently, increasing the network capacity and its cost. Cell merging process joins small and contiguous cells into a larger one, decreasing the number of required BS as well as the total network capacity.

Figure 2: Multi-tier structure of cells used by optimizer.

The constraints of the problem are the following:

\[
\begin{align*}
\sum_{i,j,k} x_{i,j,k} &\leq 1 & \forall i \in C, \forall j \in B, \forall k \in C \\
\sum_{i,j,k} y_{i,j} &\leq 1 & \forall i \in M \\
\sum_{i,j} y_{i,j} &\geq n.v & \forall i \in M, \forall j \in R \\
\end{align*}
\]
\[
\sum_{i \in B} \sum_{k \in C} x_{i,j,k} \geq y_{i,j} \quad \forall i \in M, \forall j \in R \quad (C9)
\]

\[
y_{i,j} \cdot \text{dist}_{i,j} \leq r_j \quad \forall i \in M, \forall j \in R \quad (C10)
\]

\[
\sum_{i \in M} y_{i,j} \cdot d_i \leq \sum_{i \in B} \sum_{k \in C} x_{i,j,k} \cdot c_l \quad \forall j \in R \quad (C11)
\]

\[
\sum_{f \in R} \sum_{g \in C} (x_{k,f,g} + x_{(k/q)-i,j,f,g}) \leq 1
\]

\[
\forall i, j \in N^+ | i < t, i + 1 < j \leq t, \forall k \in U_i \quad (C12)
\]

Constraints C1 and C2 state that all decision variables are binary. Constraint C3 ensures that a RAU can only be associated to a BS in a certain BSC if there is a fiber link connecting the RAU to the BSC. Constraint C4 ensures that a RAU can only be associated to a BS in a certain BSC if the BS is located at that BSC. Constraints C5 and C6 establish a one-to-one association between the RAUs and the BSs, which means that one RAU can be associated to only one BS and vice-versa. Constraint C7 ensures that each MS will be served by only one RAU. Constraint C8 guarantees that a minimum percentage of MSs will be served, which imposes a bound to network cost reduction. Constraint C9 establishes that only RAUs associated to a BS can serve users. Constraint C10 enforces that RAUs can only serve users in their coverage area. Constraint C11 limits the aggregated demand of a cell to be less or equal the BS capacity, providing criteria for minimum quality of service. Finally, constraint C12 prevents that RAUs from different tiers to be used in the same cluster.

The minimization problem aim at achieving two objectives, given by:

\[
f_1 = \min \sum_{i=1}^{m} \sum_{j=1}^{o} \sum_{k=1}^{p} x_{i,j,k}
\]

\[
f_2 = \min \sum_{i=1}^{m} w_i - \sum_{i=1}^{n} \sum_{j=1}^{o} y_{i,j} \cdot w_i
\]

The objective function \( f_1 \) represents minimization of the total operational cost. The sum of all variables \( x_{i,j,k} \) is equal to the number of associated BSs. The objective function \( f_2 \) represents the minimization of the revenue waste. Each MS belongs to a traffic class \( \omega \), which represents the revenue earned by the operator when serving a user. The first sum \( \sum_{i=1}^{m} \text{w}_i \) accounts for the maximum network revenue and the second sum accounts for the revenue of served users; the difference of the two sums is equal to the revenue waste. Instead of maximizing the revenue, the revenue waste was minimized so that \( f_1 \) and \( f_2 \) can be minimized instead of having a formulation which involves minimization and maximization of different metrics.

The optimization problem aims at minimizing the network cost \( f_1 \) as well as the revenue waste \( f_2 \), but these two objective functions are conflicting, since the minimization of one leads to the maximization of the other. Such conflicting scenario is common in multi-objective optimization problems, where the optimal solution is not unique as is in mono-objective problems, but rather it is a set of solutions [10]. An optimal set of solutions is considered Pareto optimal when the improvement of one objective function necessarily results in the worsening of at least one of the other objective functions. The set of all Pareto solutions, called Pareto frontier, represents the best compromise between the different conflicting objectives.

There are many ways of dealing with Multi-objective Optimization Problems (MOP). Heuristic-based algorithms generally give good approximations results and are fast, but depend on prior knowledge of the problem and can provide solutions far from the optimal one. Another way of solving MOP, mainly when dealing with problems yet not well investigated, as resource allocation in RoF, is by the aggregation of all objective functions, creating an Aggregated Objective Function (AOF). A common AOF is the linear weighted sum of the objective functions: \( F(f_1, f_2, ..., f_n) = \alpha f_1 + \beta f_2 + ... + \gamma f_n \), where the sum of all weights \( (\alpha, \beta, \gamma) \) must be equal to 1.

The optimization technique used in the present paper is based on the aggregation of the objective functions and the following AOF was adopted:

\[
F(f_1, f_2) = \alpha f_1 + (1 - \alpha) f_2 = \\
\alpha(\sum_{i=1}^{m} \sum_{j=1}^{o} \sum_{k=1}^{p} x_{i,j,k}) + \\
(1 - \alpha)(\sum_{i=1}^{m} w_i - \sum_{i=1}^{n} \sum_{j=1}^{o} y_{i,j} \cdot w_i)
\]

So, the final objective of the integer linear optimization problem is:  \( \text{Minimize } F(f_1, f_2) \).

IV. BI-CRITERIA ALGORITHM BASED ON RELAXATION

Although the integer linear programming (ILP) formulation yields to optimal solution, the required time can be infeasible for mobile and dynamic networks. To circumvent the time issue, we propose an algorithm that employs linear relaxation technique for finding quasi-optimal solutions in short periods. The linear relaxation consists of obtaining partial fractional solutions and, then, converting the real solutions into integer ones. The solutions based on relaxation can be considered as probability values and, by using iterative randomized rounding techniques, it is possible to transform them into integer values that satisfy the original constraints. The relaxation algorithms replace constraints C1 and C2 by C1’ and C2’.

\[
x_{i,j,k} \in [0, 1] \quad \forall i \in R, \forall j \in B, \forall k \in C \quad (C1')
\]

\[
y_{i,j} \in [0, 1] \quad \forall i \in M, \forall j \in R \quad (C2')
\]

The algorithm receives as input an initial linear programming solution. During the approximation process other linear programming problems can be executed; each execution including previous approximation decisions. The relaxation algorithm is efficient due to the fact that the time required for solving linear problems is much shorter than the time required for solving integer problems for large instances.

\[\text{Algorithm 1} \]

receives as input an initial linear optimization solution and a threshold probability value \( \text{Prob}_{thr} \). Line 1 corresponds to the initialization of the auxiliary data structure \( M' \), which stores all MSs ordered by decreasing value of revenue \( \omega \). From the top to the lowest tier (line 2), all RAUs in each tier are chosen randomly (line 3). For each
RAU, it is drawn a uniform random variable $U[0, 1]$ (line 4) that is used for the decision of associating or not the RAU to the BS with highest real value (line 5). If the highest real solution value found by the optimizer for the chosen RAU (line 6) is greater or equal to the drawn value, then the chosen RAU is associated; otherwise it is not. If the chosen RAU is associated, a new constraint is added and another execution is performed (line 7). A different constraint is added if the chosen RAU is not associated and another execution is also performed (line 13). As an attempt to circumvent possible misleading decisions, the algorithm checks whether the new linear problem becomes infeasible after the addition of the last constraints. If a constraint imposes that a specific RAU to be associated to a BS makes problem infeasible, this constraint is removed and another constraint avoiding this RAU to be associated is added (lines 8-10 and lines 22-25). If during the iteration a new RAU is chosen to be associated (line 19) and a new execution is performed, the algorithm tries to serve as many users as possible based on the probability threshold value $P_{\text{Thr}}$. The ordered list $M'$ is verified to find the highest probability value for each MS, then a new constraint (line 23) is added to the problem when a probability value greater or equal to $P_{\text{Thr}}$ is found. All served MSs are finally removed from the list $M'$ (line 24).

Algorithm 1: Linear relaxation for minimizing network cost and revenue waste

<table>
<thead>
<tr>
<th>Input:</th>
<th>Relaxed linear programming solution. $P_{\text{Prob}_{\text{Thr}}}$: threshold probability for choosing the MSs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output:</td>
<td>Integer linear programming solution.</td>
</tr>
<tr>
<td>1: Define $M'$ as a list of all MSs in decreasing order of revenue</td>
<td></td>
</tr>
<tr>
<td>2: for each tier $l$ in decreasing order of radius do</td>
<td></td>
</tr>
<tr>
<td>3: for each RAU $r$ of tier $l$ in random order do</td>
<td></td>
</tr>
<tr>
<td>4: Draw a uniform random variable between $[0, 1]$</td>
<td></td>
</tr>
<tr>
<td>5: Find the highest probability $x_{r,j,k}, \forall j \in B$ and $\forall k \in C$</td>
<td></td>
</tr>
<tr>
<td>6: if highest probability $(x_{r,j,k}) &gt; \text{drawn value}$ then</td>
<td></td>
</tr>
<tr>
<td>7: Add constraint $x_{r,j,k} = 1$ and run again the relaxed linear programming problem</td>
<td></td>
</tr>
<tr>
<td>8: if new problem is infeasible then</td>
<td></td>
</tr>
<tr>
<td>9: Remove constraint $x_{r,j,k} = 1$</td>
<td></td>
</tr>
<tr>
<td>10: Add constraint $\sum_{\forall p \in C} \sum_{\forall o \in B} x_{r,o,p} = 0$</td>
<td></td>
</tr>
<tr>
<td>11: end if</td>
<td></td>
</tr>
<tr>
<td>12: else</td>
<td></td>
</tr>
<tr>
<td>13: Add constraint $\sum_{\forall p \in C} \sum_{\forall o \in B} x_{r,o,p} = 0$ and run the linear programming problem</td>
<td></td>
</tr>
<tr>
<td>14: if new problem is infeasible then</td>
<td></td>
</tr>
<tr>
<td>15: Remove constraint $\sum_{\forall p \in C} \sum_{\forall o \in B} x_{r,o,p} = 0$</td>
<td></td>
</tr>
<tr>
<td>16: Add constraint $x_{r,j,k} = 1$</td>
<td></td>
</tr>
<tr>
<td>17: end if</td>
<td></td>
</tr>
<tr>
<td>18: end if</td>
<td></td>
</tr>
<tr>
<td>19: if a new RAU was associated in the current iteration then</td>
<td></td>
</tr>
<tr>
<td>20: for all MS in list $M'$ do</td>
<td></td>
</tr>
<tr>
<td>21: Find the highest probability $y_{i,j} \forall j \in R$</td>
<td></td>
</tr>
<tr>
<td>22: if highest probability $(y_{i,j}) &gt; P_{\text{Prob}_{\text{Thr}}}$ then</td>
<td></td>
</tr>
<tr>
<td>23: Add constraint $y_{i,j} = 1$</td>
<td></td>
</tr>
<tr>
<td>24: Remove MS $i$ from list $M'$</td>
<td></td>
</tr>
<tr>
<td>25: end if</td>
<td></td>
</tr>
<tr>
<td>26: end for</td>
<td></td>
</tr>
<tr>
<td>27: end if</td>
<td></td>
</tr>
<tr>
<td>28: end for</td>
<td></td>
</tr>
<tr>
<td>29: end</td>
<td></td>
</tr>
</tbody>
</table>

V. NUMERICAL RESULTS

The RoF network infrastructure considered in all the experiments is shown in Figure 3. It consists of one BSC, several RAUs distributed uniformly in an area of 2Km x 2Km and a varying number of BSs and MSs. RAUs are organized in a multi-tier fashion with 4 tiers and clusters with 4 cells. The highest tier (tier one) consists of a single RAU with radius of 1420m. The second tier consists of 4 RAUs with radius of 710m, disposed in a grid 2 x 2. The third tier has 16 RAUs with radius of 360m. The lowest tier (fourth one) involves 64 RAUs with radius of 180m. RAUs of two different tiers cannot operate simultaneously to cover a certain area.

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

The optimization model was implemented using the C programming language and the optimization library FICO Xpress 7.0 [11], which implements LP-based Branch and Bound for solving integer linear programming problems. All experiments were executed in a workstation with Intel Core 2 Quad core processor at 2.6 GHz, 3 GB of RAM and Debian GNU/Linux kernel 2.6.23.1 operating system. The location of MSs was set according to Random Trip Model [12] with a real urban scenario of Houston, Texas/USA.

In the experiments, four different types of network infrastructures were considered: Infrastructure 1 involved only the lowest tier of RAUs (64 RAUs); Infrastructure 2 consisted of the lowest 2 tiers (64 + 16 RAUs); Infrastructure 3 was composed by 3 tiers (64 + 16 + 4 RAUs); and Infrastructure 4 involved all 4 tiers (64 + 16 + 4 + 1 RAUs). In all experiments, the minimum percentage of served users $(\nu)$ was set to 0 (zero); the capacity $(C)$ of all BSs was set to 30 and the demand $(D)$ of all MSs was set to 1; finally, the class $(W)$ of all MSs was set to 1.

A. Pareto optimal solutions analysis

Integer solutions were found, varying the weight $\alpha$ from 0 to 1 in steps of 0.05. It is known that a uniformly distributed set of weights does not necessarily produce Pareto solutions uniformly distributed in the Pareto frontier [13] and that this method may not be able to generate all solutions of non-convex Pareto frontiers. The experiments showed, however, that the Pareto frontier for such problem is convex and that optimal solutions are well distributed in the solution space. In order to normalize the significance of the weights variation for each objective, the final objective function was changed to:

$$F'(f_1, f_2) = \alpha \left( \frac{f_1 - f_{1\text{min}}}{f_{1\text{max}} - f_{1\text{min}}} \right) + (1 - \alpha) \left( \frac{f_2 - f_{2\text{min}}}{f_{2\text{max}} - f_{2\text{min}}} \right)$$
where, $f_i^{\min}$ and $f_i^{\max}$ are, respectively, the minimum and maximum values of objective function $f_i$.

Simulations were executed with the aggregated objective function $F' (f_1, f_2)$ for networks with up to 500 MSs and for the 4 different types of infrastructures. Results can be seen in Figures 4, 5 and 6. Results using Infrastructure 4 were very similar to the results using Infrastructure 3, except for networks with less than 30 MSs, since the fourth layer (larger cell) is only activated when the network demand is smaller than the BS capacity (30 MSs).

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Infrastructures 1 and 2 were used, demand 9, 21, 25 and 30 BSs; and 3, 7, 9 and 12 BSs, respectively.

![Fig. 5: Pareto frontier of a network with up to 500 MSs, using Infrastructure 2](image)

The network operational cost (Figure 4) when considering Infrastructure 1 involves almost 55 RAUs for networks with 500 MSs with no revenue waste. Moreover, when using Infrastructure 2 and Infrastructure 3, it is possible to obtain the same revenue but with only 22 BSs (Figures 5 and 6). A cost reduction greater than 50% to obtain the same revenue when comparing to Infrastructure 1 (Figure 4) can be noticed. Networks with 100, 200, 300 and 400 MSs, when

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Results for Infrastructure 2 and for Infrastructure 3 are similar when considering networks with more than 100 MSs; this happens because networks with less than 120 MSs can be well designed with the four RAUs of tier 3. For networks with up to 100 MSs, however, it is possible to verify a significant cost reduction (Figures 5 and 6). Using Infrastructure 3, it was possible to serve all MSs (no revenue waste) with only 6 BSs, while it was required up to 14 BSs when using Infrastructure 2, for networks with up to 100 MSs.

The greatest network cost reduction was found when using Infrastructure 3, but it demanded more computational effort to find solutions. The required time increased proportionally to the number of MSs. For a certain number of MSs, however, the required time to obtain optimal results depends on the weight values. Weight values close to 0 or to 1 demanded less time for solving the problem, while weights between 0.3 and 0.7 demanded the most.

B. Approximated results analysis

In order to verify the effectiveness of Algorithm 1, the same set of scenarios simulated previously was used. The input probability threshold was set to 0.9. Algorithm 1 produced results close to the optimal for all infrastructures, with significant time reduction, with the greatest reduction obtained for Infrastructure 3 and Infrastructure 4. Reductions greater than 25 times in the computational duration were obtained. Figure 7 shows the approximated results and the Pareto frontier (Figure 6).

In Figure 7, it is clear that most of the results given by Algorithm 1 are very close to the optimal frontier. For networks with up to 200 MSs, results are practically the same as the optimal ones. Results for networks with 300, 400 and 500 users are located above the Pareto frontier, not far from the optimal results.
Finally, Figure 8 shows for Infrastructure 3 the mean computational time required to produce both the optimal and the approximated solutions. The computation accounted the results obtained with different weights (from 0 to 1). Figure 8 shows results with confidence intervals of 95% of confidence levels. For networks with up to 100 MSs, both solutions roughly demanded the same duration to be derived, but for network with more than 200 MSs, the large difference in the required time is evident. The integer algorithm required up to 25 times more to produce results than did the algorithm based on relaxation. It is also clear that the variance of the required time to produce results by the integer algorithm is high. As mentioned before, the computation of results with weight values close either to 0 or to 1 were fast derived and the computations with weight values close to 0.5 were very slow.

VI. Conclusion

In this paper, we introduced a centralized resource optimization model, which involves dynamic cell splitting and merging executed for multi-tier RoF infrastructures of RAUs. The optimization problem aims at two different objectives and uses a bi-criteria objective function that simultaneously reduces the network operational cost and maximizes the operator revenue. An algorithm based on relaxation was also proposed for obtaining fast solutions. This algorithm produced results very close to the optimal ones requiring much less computational effort.

The Pareto frontier can be used by network operator as guidelines for dynamic network optimization. The low computational time demanded by the algorithm based on relaxation showed that it is feasible to optimize radio resources in mobile networks in real time.

Acknowledgment

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