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A computationally efficient method for QoE-driven self-planning of antenna tilts in a LTE network

P. A. SÁNCHEZ[1], S. LUNA-RAMÍREZ[1], M. TORIL[1]
[1]Departamento de Ingeniería de Comunicaciones, Universidad de Málaga, 29010, Málaga, Spain.
Corresponding author: S. Luna-Ramírez (e-mail: sluna@ic.uma.es).

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ABSTRACT In future mobile communications systems, network management procedures must be upgraded to consider user quality of experience (QoE) to deal with service diversity. In this work, a computationally efficient centralized method for determining the best configuration of antenna tilts when planning a LTE network is presented. Unlike previous network-centric methods, the proposed self-planning method is driven by QoE criteria. The core of the method is the grouping of cells into clusters without mutual interference, which speeds up the search for the optimal solution with a classical steepest descent algorithm. Method assessment is carried out in a static system-level simulator adjusted with real connection traces. For this purpose, traffic demand in the scenario is broken down per location and service to estimate the QoE obtained by each antenna tilt plan. During the analysis, the method is compared with legacy tilt planning approaches. Results show that the proposed method achieves a near-optimal solution for the overall system QoE with a computational cost lower than state-of-the art algorithms previously reported in the literature.

INDEX TERMS LTE, self-planning, antenna tilt, traces, QoE

I. INTRODUCTION

THE evolution of services offered by operators have radically transformed mobile networks, making cellular network management a very complex task. Such a trend will continue in the coming years with the new applications and services supported by 5G systems [1], [2]. To deal with network complexity, operators require automated network management tools including Self-Organizing Networks (SON) techniques [3].

One of the most critical tasks in cellular network management is determining the right size of each cell in the network. Insertion of base stations (e.g., new site) or changes in the environment (e.g., new buildings) require constantly updating cell footprints. This problem, referred to as Coverage and Capacity Optimization (CCO), has been identified as a relevant SON use case [4]. In practice, cell footprint can be controlled by changing parameters of the base station, such as height, transmit power [5]–[7] or antenna bearings (i.e., tilt [8]–[14] and/or azimuth [15]–[17]). The introduction of Remote Electrical Tilt (RET) has made antenna tilting the preferred option. Nonetheless, finding the optimal tilt of every single antenna in the network is a challenging task due to the large number of base stations and complex relationship between the performance of neighbor cells. The underlying large-scale optimization problem is not separable, since the best tilt for a cell depends on neighbor settings. Even when considering a small cluster of cells, the large size of the solution space prevents the use of exact algorithms. Moreover, deriving a closed-form expression relating individual tilt angles to the overall network performance is also difficult, since a trade off exists between signal quality for cell-edge users and interference over users in neighbor cells.

Tilt-based CCO methods can be grouped into self-planning and self-optimization schemes. Self-planning methods rely on analytical or simulation models to estimate network performance obtained by a tilt plan. With these models, sophisticated search algorithms can be used to find the optimal tilt plan. In contrast, self-optimization methods use the real network to check the impact of small tilt changes selected by heuristic rules. In both schemes, a network-centric approach focused on network performance is often adopted. Thus, the figure of merit used to assess the quality of a tilt plan is derived from signal quality indicators, such as signal-to-noise-plus-interference ratio (SINR) on cell edge and cell center. In the last years, the launch of multimedia services have forced mobile operators to update network management towards a user-centric approach focused on Quality of Experience (QoE) [18]. Thus, it is widely accepted that end user experience must be considered in the design and operation of future 5G systems [19], [20]. For this purpose, operators can leverage big-data empowered SON platforms to analyze data collected on a per-connection basis in different network interfaces [21]. Nonetheless, estimating user satisfaction from network performance measures is not straight forward, especially in radio network planning. The main difficulty is modeling dynamic packet scheduling in the base station with services of very different nature, to derive user throughput per location and service. Thus, most automatic planning schemes are still driven by signal quality estimates.

In this work, a computationally efficient iterative method for determining the best configuration of antenna tilts when (re)planning a LTE network is presented. As in most planning methods, network performance is estimated by analytical means. However, unlike legacy network-centric approaches, the proposed method is driven by QoE criteria. The core of the method is the grouping of cells into clusters with no mutual interference, which speeds up the search for the optimal solution with a classical steepest descent algorithm. Method assessment is carried out in a static system-level simulator adjusted with real connection traces. For this purpose, traffic demand in the scenario is broken down per location and service to estimate the QoE obtained by each antenna tilt plan. During the analysis, the method is compared with state-of-the-art methods, namely rule based [14] or Taguchi [17] method. Results show that the proposed method achieves a near-optimal solution for the overall system QoE with a computational cost significantly lower than algorithms previously reported in the literature. The rest of the paper is structured as follows. Section II revises related work. Section III outlines the system model. Section IV formulates the antenna tilt planning problem. Section V describes the proposed self-planning method. Section VI presents the experiments carried out to assess the method. Finally, Section VII presents the main conclusions of the work.

II. RELATED WORK

CCO by antenna tilting has been widely cover in the literature. Preliminary studies cover basic radio aspects in a tilted cell [22], [23]. Later studies check the impact of tilting on system performance by simulations [24]–[28] or field trials [29], [30]. These studies are the basis of CCO methods

In the deployment stage, self-planning (a.k.a. self-configuration) schemes use network performance models to check the quality of a parameter plan [10]–[12], [14], [17], [31]–[38]. To find the best tilt plan, some methods use exhaustive search (e.g., brute-force enumeration [11]) to ensure optimality at the expense of a large execution time. To speed up computations, other methods use advanced meta-heuristics (e.g., Taguchi [17], genetic [12], evolutionary [31], particle swarm [32]...) to efficiently explore the solution space in the search for near-optimal solutions. Alternatively, some methods use local search algorithms (e.g., coordinate descent [33], Nelder-Mead [34], gradient descent [14], [35], simulated annealing [36], case-based learning [10], Tabu search [37], primal-dual [38]...). These algorithms start with an initial solution that is progressively refined by introducing small changes. Thus, they achieve high-quality solutions if they are not trapped in local minima.

In the operational stage, self-optimization (a.k.a. self-tuning) schemes [5], [7], [14], [39]–[45] take advantage of live measurements to dynamically adapt network parameters to changing network conditions. For this purpose, a controller iteratively modifies network parameters based on continuous performance measurements (e.g., cell load or inter-cell interference) without the need for a network model. The controller can be an equation solver [5], [39], a local search algorithm [7], [40], a heuristic rule-based controller [14], [41] or an adaptive controller adjusted by reinforcement learning [42]–[45]. These can be implemented as a centralized entity to reduce communication overhead or as a distributed entity to share computational load among base stations.

All the above methods adopt a network-centric approach focused on network performance. To the authors' knowledge, the only work on tilt-based CCO that explicitly considers service performance is [46], where a voice QoE model is used to adjust antenna tilts with a particle swarm algorithm. Hence, no work has evaluated QoE-driven tilt optimization in a multi-service environment.

The main contributions of this work are:

1) The inclusion of QoE criteria when adjusting antenna tilts in a multiservice cellular scenario, unlike [46], where only a single service is considered (i.e., voice). Note that optimal tilt settings may not be the same for all services, requiring a trade-off among services, which makes the search for the optimal solution more complicated. By evaluating the QoE of each service, the proposed tilt plan maximizes the overall system QoE.
2) The grouping of cells into clusters with no mutual interference in a classical gradient-based algorithm, which speeds up the search for the optimal solution by ensuring steps in orthogonal directions.
3) The assessment of solutions in terms of QoE with the analytical system model described in [47]. Note that the proposed method is conceived for the network design stage, when no QoE measurements are available. Thus, the impact of tilt changes on QoE has to be evaluated with a network performance model, which in most cases relies on computationally expensive Monte-Carlo simulations. The proposed analytical approach for evaluating solution quality reduces execution time and can be applied to any self-planning algorithm driven by QoE criteria.

III. SYSTEM MODEL

Most radio network planning tools divide the geographical area under analysis into a grid of points. Each point denotes a potential user, generating a data volume of a limited set of services. Unlike previous work, user satisfaction is measured here in terms of QoE, reflected as Mean Opinion Scores (MOS), ranging from 1 (bad) to 5 (excellent) [48].

The QoE experienced by a user of a service is estimated from Quality-of-Service (QoS) indicators measured on a user and service basis. For data hungry services (e.g., web, video streaming or file sharing), QoS is given by average user throughput, which can be mapped into QoE values by means of utility functions specifically defined for each service. Without loss of generality, only the above-mentioned services are considered here for simplicity. Average user throughput is computed per location and service with the system-level simulation tool described in [47]. For this purpose, an analytical performance model of dynamic packet scheduling is used, including service differentiation and the consideration of last Time Transmission Interval (last-TTI) transmissions. More details about the simulation tool can be found in [47].

Then, the assessment of a tilt plan is based on QoE indicators. Two metrics are used to reflect the coverage-capacity trade-off. A first figure of merit reflecting network capacity is the global QoE, defined by a weighted average of cells in the scenario as

$$QoE_{global} = \frac{\sum_{c} N_{conn}(c)\, QoE_{cell}(c)}{N_{conn,T}} , \tag{1}$$

where $N_{conn}(c)$ is the number of connections in cell c, $N_{conn,T}$ is the total number of connections across the network (i.e., $N_{conn,T}{=}\sum_{c} N_{conn}(c)$). $QoE_{cell}(c)$ is the average QoE of users in cell c, defined as

$$QoE_{cell}(c) = \frac{\sum_{u\in c} D(u)\, QoE_{user}(u)}{\sum_{u\in c} D(u)} , \tag{2}$$

where $D(u)$ is the data volume of user u in cell c and $QoE_{user}(u)$ is the QoE experienced by user u (in cell c), calculated as

$$QoE_{user}(u) = \frac{\sum_{s} D(s,u)\, QoE(s,u)}{\sum_{s} D(s,u)} , \tag{3}$$

where $D(s,u)$ is the data volume of user u (in cell c) for service s, and $QoE(s,u)$ is the QoE experienced by user u (in cell c) for service s. The latter is calculated from service performance indicators (e.g., download time for web surfing/file sharing or initial buffering time for video streaming) with utility functions defined on a per-service basis. The utility function defined for each service is detailed in [47].

A second figure of merit reflecting network coverage is the 5[th] percentile of the QoE_{user} distribution across the network, $QoE_{user}^{(5th)}$. This value is obtained by sorting $QoE_{user}(u)$ values in the scenario and aggregating their data volume until 5% of the total network data volume is reached, i.e., $QoE_{user}^{(5th)} = QoE_{user}(u_{5th})$, where u_{5th} is the first user fulfilling that

$$\frac{\sum_{u=1}^{u_{5th}} D(u)}{\sum_{u} D(u)} \geq 0.05 \ . \tag{4}$$

Note that, in (4), users are ranked from lower to higher $QoE_{user}(u)$ values.

Both figures of merit reflect MOS values. Thus, QoE improvements are measured in MOS points.

IV. PROBLEM FORMULATION

The CCO problem is formulated as the optimization problem

$$\max_{\alpha(c)} \ QoE_{global} \tag{5}$$

$$\text{s.t.} \ \ 0 \leq \alpha(c) \leq \alpha_{max} \quad \forall\, c \tag{6}$$

$$\sum_{u} D(u) = D_T \tag{7}$$

$$\sum_{c} X(u,c) = 1 \quad \forall\, u \ . \tag{8}$$

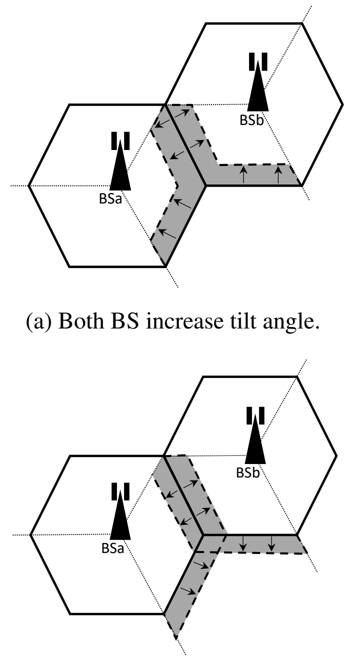
The decision variables are the antenna tilt angles, $\alpha(c)$, ranging from a minimum value (i.e., 0° when the antenna is aimed at the horizon) to a maximum value, α_{max}, defined by the vendor. Eq. (5) reflects the goal of maximizing the overall network QoE. Eq. (6) reflects physical antenna limitations. Eq. (7) enforces that the total user data volume remains fixed with tilt changes across iterations. The aim of this constraint is a fair comparison of performance indicators across iterations. Finally, (8) ensures that every user is served by just one cell (a.k.a. single homing). To this end, a binary variable, $X(u,c)$, is defined, so that $X(u,c) = 1$ if user u is served by cell c, and 0 otherwise.

The problem in (5)-(8) is a high-dimensional non-separable non-convex optimization problem. Specifically, the size of the solution space in tilt-based CCO is ${N_\alpha}^{N_c}$, where N_α is the number of possible tilt angles and N_c is the number of cells. The huge number of combinations makes brute-force enumeration infeasible even for small scenarios. Thus, tilt optimization has to be solved by numerical methods. In these methods, computational efficiency is critical, since they follow an iterative solution procedure. This is achieved by minimizing the number of solutions to be tested. Unfortunately, non-separability makes the selection of candidate solutions more complicated.

Starting with the antenna aimed at the horizon, the larger tilt in a cell c, $\alpha(c)$, the higher signal level received in the area served by the antenna and the lower interference received by neighbor cells. This antenna movement causes an increase of signal quality, spectral efficiency and throughput for users in the modified cell, translated into a better user experience. In parallel, cell coverage area is reduced by downtilting. If the antenna is downtilted beyond the actual cell edge, there may be some distant users receiving insufficient signal power, which are handed over to another cell if enough cell overlapping exists. Otherwise, a coverage hole is created, with the subsequent degradation of user experience. Conversely, a smaller tilt angle might solve coverage gaps, but may lead to excessive interference in neighbor cells.

From the above explanation, it is clear that tilt changes must be coordinated between neighbor cells. As an example, Figure 1 shows the result of a naive planning algorithm where tilt analysis is applied independently between two neighbor cells (sectors), BSa and BSb, located in nearby sites. First, the algorithm checks the impact of increasing the tilt angle (i.e., downtilting) of BSa by 1 degree. This change reduces BSa service area (dashed line in the figure). Users in the old cell edge (shaded area in the figure) are excluded, while users still in BSa after antenna movement experience a better performance. On the other side, users in the shaded area are handed over to BSb, but their performance is similar to (or slightly worse than) that when assigned to BSa. Thus, the global performance for this two-cell scenario would improve with this antenna movement. Hence, the algorithm decides to downtilt BSa by 1 degree. Following a similar reasoning, in an independent and later decision, an increase in BSb tilt angle is also suggested. As a result, two downtilt actions are decided, even if each individual decision is assessed in a wrong scenario as if only one antenna was modified. Figure 1a illustrates cell service areas when both downtilt changes are implemented. It is observed that shaded areas are excluded from BSa and BSb, causing a coverage hole, and degrading the overall system performance. The opposite case is represented in Figure 1b, where the uncoordinated movements of both cells create a very large area of overlap, unnecessarily increasing inter-cell interference, while also degrading the overall system performance.

To circumvent cell coupling, tilt planning can be approximated by combining multiple regular scenarios built on a per-adjacency basis [49]. Such a regularization approach requires solving $N_\alpha \times N_c$ optimization problems, where N_α is the number of possible angles and N_c the number of cells, with a single decision variable (i.e., the tilt angle of the cell under study), which is much easier than solving the original multi-dimensional problem. However, such an approach has no guarantee on the quality of the final solution. Another approach is to evaluate the impact of tilt changes one at a time (i.e., sequentially). In this approach, the algorithm first evaluates and changes tilt in BSa, and then evaluates tilt changes in BSb with the new tilt of BSa. This ensures that the impact of every tilt change is properly estimated, but increases the computational load, as all cells must be re-evaluated after every single parameter change. More importantly, the number of iterations grows exponentially as changes are restricted to a single antenna per step. In this work, a different approach is taken based on defining groups of cells with no mutual interference.



(a) Both BS increase tilt angle.

(b) Both BS decrease tilt angle.

FIGURE 1: Naive tilt planning algorithm.

V. SOLUTION ALGORITHM

The rationale of the algorithm is explained first and the details of the algorithm are presented later.

A. RATIONALE OF THE ALGORITHM

To solve the above problem, any classical gradient-based algorithm can be used. A first option is gradient (or Steepest) Descent (SD), which is an iterative algorithm for finding a local minimum of a differentiable function [50]. SD starts with an initial tilt plan, $\alpha^{(0)}(c)$, which is progressively refined by small steps, $\Delta\alpha(c)$, proportional to the negative of the gradient of the objective function in (5). However, SD slowly converges to the optimal solution in non-separable problems where the objective function depends on interaction between decision variables. This is the case of tilt planning, as QoE in a cell depends on the tilts of all neighbor cells. Note that changes in antenna tilt have a direct impact on the service areas of the modified cell and their neighbors [51]. Such a dependence causes that any tilt change in a cell often requires updating the tilt of neighbor cells in subsequent iterations. Alternatively, the conjugate gradient (CG) algorithm selects small steps in orthogonal directions, which speeds up the search for the optimal solution [50]. Based on this orthogonality principle, a simple gradient-based algorithm is proposed here that minimizes the number of updates in the search by ensuring that tilt changes introduced at any iteration do not affect neighbor cells. This is achieved by grouping cells into clusters with no mutual interference.

The aim is to divide the scenario into N_g antenna groups ($<N_c$). These groups, of different size, consist of decoupled antennas, i.e., spaced-apart antennas that do not interfere with each other. Thus, antenna movements within the group have no impact on other antenna movements in the group. Such a decoupling allows starting the analysis of every antenna movement without taking into account movements of other antennas in the group. Once tilt changes in a group have been implemented, next group is defined and adjusted. Cells in the next group are usually coupled with cells in the previous one, and, thus, performance evaluation has to consider tilt changes in the previous group. The process continues until all antenna groups have been adjusted, and it is repeated several times until some convergence criterion is met. For clarity, the analysis of a group is hereafter referred to as a *step*, and the analysis of all groups is referred to as an *iteration*.

B. ALGORITHM OUTLINE

The method proposed here uses a gradient-based iterative algorithm that takes advantage of radio decoupling between distant cells to speed up the search for the optimal solution (hereafter denoted as Decoupled Cells algorithm, DC). The aim is to find the maximum of an objective function (i.e., the global QoE) by incorporating gradient estimates from finite differences. In its simplest version, the search starts from an initial tilt configuration, which is updated at iteration $(n+1)$ with gradient estimates for that cell as

$$\begin{aligned} \alpha^{(n+1)}(c) &= \alpha^{(n)}(c) + \Delta\alpha^{(n)}(c) \\ &= \alpha^{(n)}(c) + k\, \nabla\widehat{QoE_{global}}^{(n)}(c) \\ &= \alpha^{(n)}(c) + k\, \frac{\delta \widehat{QoE_{global}}^{(n)}}{\delta\alpha}(c)) \,, \end{aligned} \tag{9}$$

where k is a gain constant.

To compute gradient estimates, a straight-forward approach is to introduce small changes in each individual component of the decision variable (i.e., tilt of a single cell) one at a time (Kiefer-Wolfowitz algorithm [52]). Alternatively, some methods simultaneously change all parameter components using a random variable distribution to reduce the number of function evaluations (simultaneous perturbation stochastic algorithm [53]). Similarly to the latter, the proposed algorithm changes several tilt parameter simultaneously, but ensures that the selected cells are decoupled. For this purpose, the scenario is divided into some number of groups of distant cells, so that changes in cells belonging to the same group do not affect other cells in the same group. Thus, tilt modifications can be implemented simultaneously without the need for reevaluating system performance.

DC follows an iterative process consisting of an external loop (iterations) and an internal loop (steps). The external loop is illustrated in Figure 2, where every new execution is

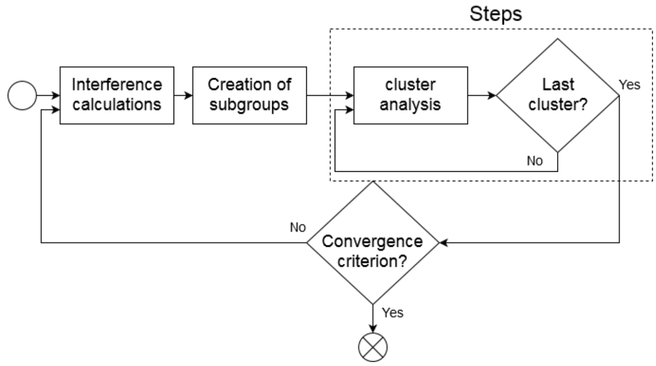


FIGURE 2: Flow diagram of the DC algorithm.

an iteration. The first task is the calculation of cell mutual interference. For every cell in the scenario, a list of the N_{int} most interfering neighbor cells with the current tilt plan is generated. Based on these lists, antenna groups are defined. A group is defined by those cells that are not in any interference list for any other cell in the group, i.e., any couple of cells selected in a group experience a negligible mutual interference (i.e., less than the N_{int} most interfering cells). Different groups can have a different number of cells. At this point, N_g groups are defined. Then, the internal loop (referred to as step) computes tilt changes for every group. The iteration ends when all groups have been analyzed.

C. CLUSTERING ALGORITHM

A straight-forward approach to define groups of decoupled cells is by geometric means. Such an approach only considers site locations and antenna azimuths, thus requiring no explicit calculation of mutual interference. The resulting groups are static, thus requiring no update in subsequent iterations. However, interference levels are strongly affected by tilt changes, causing that the most significant interfering cells change with iterations.

Instead, a simple heuristic clustering algorithm based on interference levels is used here. For every cell in the scenario, a list of the N_{int} most interfering neighbor cells with the current tilt plan is generated. This is achieved by selecting neighbors causing the lowest average signal-to-interference-plus-noise ratio (SINR) in the dominance area of a serving cell when only the interference from that neighbor is taken into account. SINR is computed per location with a system-level simulation tool. Based on these lists, an arbitrary number of antenna groups, N_g, will be formed. In each group, a first seed antenna (cell) is selected and other antennas are added if they are not included in the interferer list of cells already in the group. The process continues by selecting one of the unassigned antennas as seed of a new group, until all antennas belong to a group. Note that groups can have a different number of antennas, and a different number of groups can result at every iteration. The number of groups depends on the parameter N_{int}, which must be large enough to ensure that all significant interferers are included in the list. In this work, $N_{int} = 20$, which is large enough to ensure that antennas in the same group have negligible mutual interference in typical scenarios. Also note that the maximum number of groups is N_{int}, so that clustering is done in, at most, N_{int} steps.

An example of how to define one group of non-interfering cells, $\mathbb{S}_1$, is detailed next. It starts from an ordered list of all cells in the scenario, $\mathbb{C}$. From this list, a randomly selected cell, s_1, becomes the first cell of $\mathbb{S}_1$. Later, the set of interferers of cells in the group is initialized with the 20 most interfering cells of s_1, $\mathbb{I}\{s_1\}$. Next, the candidate cell set, $\mathbb{C}$, is updated as:

$$\mathbb{C}' = \mathbb{C} - s_1 - \mathbb{I}\{s_1\} \,. \tag{10}$$

Then, a new cell, s_2, is searched in $\mathbb{C}'$, such that it meets the condition

$$s_1 \not\subset \mathbb{I}\{s_2\} \,. \tag{11}$$

The first cell in $\mathbb{C}'$ that meets this condition becomes a member of $\mathbb{S}_1$ and the set of interferers is updated with the interferers of s_2. This process continues until $\mathbb{C}' = \emptyset$. The same process is repeated for the following cell groups, $\mathbb{S}_i$, with the constraint that cells already belonging to a previous group are not available for selection. With this process, N_g groups of variable length are obtained. Note that N_g is not pre-defined but a result of the clustering algorithm.

For best accuracy, cell groups should be recalculated after every change of tilt settings (i.e., after every step). Instead, cell groups are updated only after every iteration to ensure that all cells are tuned once per iteration. Thus, the computational load of clustering is negligible.

The internal loop is illustrated in Figure 3, where iteration index is omitted for clarity. Tilt changes in cells of a group are computed on a cell-by-cell basis. First, the algorithm estimates the change in QoE when tilt angle in cell c is increased or decreased by 1 degree. This is done by comparing system performance in the vicinity of the cell under analysis before and after implementing the changes. For computational efficiency, it is assumed that the impact of adjusting the antenna of a cell is restricted to its closest neighbors (hereafter referred to as *cluster* of a cell; not to be confused with the group of cells involved in the search algorithm). The QoE in the cluster of cell c is defined as the weighted sum of the QoE of cell c and its most important neighbors, as

$$QoE_{cluster}(c) = \frac{N_{conn}(c)\, QoE_{cell}(c) + \sum\limits_{v \in V(c)} N_{conn}(v)\, QoE_{cell}(v)}{\sum\limits_{v \in V(c)} N_{conn}(v)} \,, \tag{12}$$

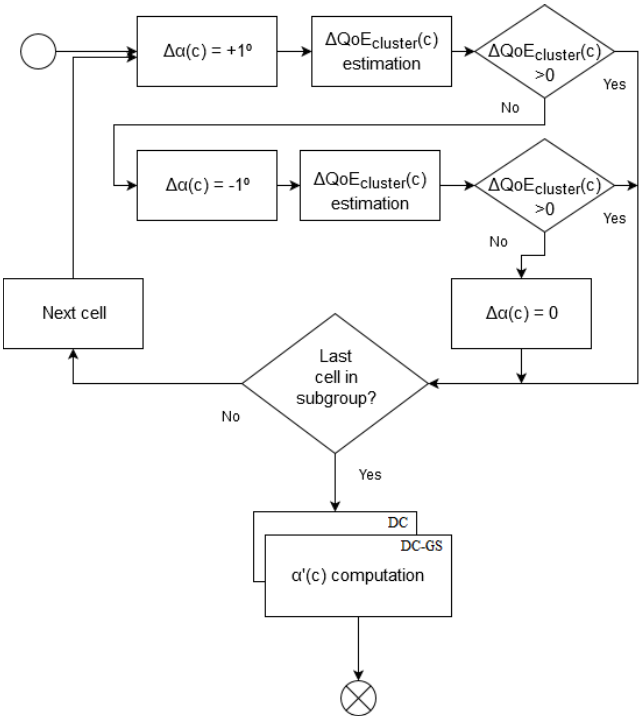


FIGURE 3: Flow diagram of internal loop.

where v is the neighbor cell index and $V(c)$ is the set of relevant neighbors of cell c. Accordingly, $\Delta QoE_{global} \approx \Delta QoE_{cluster}(c)$. Then, the selected action for that cell (increase, decrease or no change) is that leading to a better system performance (i.e., $\Delta QoE_{cluster}(c) > 0$).

In this work, $\triangle\alpha(c) \in \{-1°, 0°, +1°\}$, ensuring an adequate trade-off between system stability and convergence speed. As a final stage, the new tilt angle for cell c is calculated as in (9). At this point, two variants of the algorithm are defined, differing in the gain constant:

1) DC: the tilt change in each cell is proportional to the QoE increase obtained by the selected action in its cluster, normalized by the largest improvement achieved by a cell of the scenario, i.e.,

$$\triangle\alpha_{DC}(c) = \frac{\triangle QoE_{cluster}(c)}{\max\limits_{c}\left(\triangle QoE_{cluster}(c)\right)} \triangle\, \alpha(c) \,. \tag{13}$$

Note that $\triangle\alpha(c)$ in (13) equals $+1°$,$-1°$ or $0°$, if the selected action is increase, decrease or no change in the tilt angle, respectively. Briefly, $\triangle\alpha(c)$ is related to the expected QoE improvement to favor changes with a larger impact on system QoE, as in a gradient ascent algorithm. At the same time, normalization aims to limit the magnitude of changes to ensure stability. Thus, tilt angle changes are bounded in the interval [min($\triangle\alpha(c)$), max($\triangle\alpha(c)$)] (i.e., $[-1°, +1°]$ in this work). It should be pointed out that, for convergence reasons, the value of $\max\limits_{c}\left(\triangle QoE_{cluster}(c)\right)$ is calculated at the end of the first iteration, and remains fixed for the following iterations, in the hope that the magnitude of tilt changes decreases for subsequent iterations.

2) DC-GS: In this case, a heuristic Gain Scheduling (GS) algorithm is used to derive tilt changes, as

$$\triangle \alpha_{GS}(c) = \max\left(\beta \frac{\triangle QoE_{cluster}(c)}{\max\limits_{c}\left(\triangle QoE_{cluster}(c)\right)}, \gamma\right) \triangle \alpha(c) \ , \quad (14)$$

where β and γ are gain factors, shared by all cells, introduced to improve convergence to the final solution, as in many feedback control systems. Such gains are initially set to large values (e.g., $\beta = 3.5$ and $\gamma = 1.5$) to allow large tilt changes to ensure that the algorithm explores large portions of the solution space. Then, gains are progressively reduced to ensure stability. Specifically, gain factors are decreased for a group of cells if the decoupling assumption is not valid anymore. This is detected by evaluating the condition

$$\frac{\left|\sum\limits_{c \in \mathbb{S}_i(c)} \triangle QoE_{cluster}(c) - \sum\limits_{c \in \mathbb{S}_i(c)} \triangle QoE_{sim}(c)\right|}{\sum\limits_{c \in \mathbb{S}_i(c)} \triangle QoE_{cluster}(c)} < 0.3 \ , \quad (15)$$

where $\mathbb{S}_i(c)$ is the set of cells in the group to which cell c belongs, and $\triangle QoE_{sim}(c)$ is the change in the system QoE when all tilt changes in the group are implemented simultaneously. If (15) is satisfied, new values of β and γ are computed as

$$\beta' = \max(\, 0.85\, \beta \, , \, 1) \text{ and} \quad (16)$$

$$\gamma' = \max(\, 0.9\, \gamma \, , \, 0.5) \ , \quad (17)$$

where β' and γ' are the new values of gain factors for the next step.

Both algorithms stop when a certain convergence criterion is met. In this work, iterations continue until

$$|\triangle QoE_{global}|^{(n)} = QoE_{global}^{(n)} - QoE_{global}^{(n-1)} \leq 0.005 \ . \quad (18)$$

D. COMPUTATIONAL ISSUES

The theoretical worst-case time complexity of the algorithm should be close to that of non-linear conjugate gradient algorithm [54]. Thus, the number of iterations to convergence grows linear with the number of decision variables (i.e., antennas or cells). In each iteration, calculations include gradient estimation and cell clustering. Cell clustering is extremely simple. In contrast, the gradient estimation requires perturbation operations involving the analytical simulator, which are repeated per cell. In this operation, the most time consuming task is interference calculation, which has to be done on an adjacency basis. Thus, the worst-case time complexity of interference calculations is $O(N_c^2)$, where N_c is the number of cells in the scenario. Interference estimates are updated after changing the tilt settings of each cell group, which takes place N_g times per iteration, where N_g is the number of decoupled cell groups. Thus, the overall algorithm complexity is $O(N_g N_c^2)$.

In practice, method convergence is improved by restricting the maximum tilt change per iteration to 1°, which ensures an adequate trade-off between system stability and convergence speed. Larger values are not selected because of the high sensitivity of network performance (and user QoE) to antenna tilt changes. This would require updating interference statistics more frequently during the optimization process, which would increase computational load. On the other side, vendors offer the possibility of tilting the antenna in smaller changes (e.g., +/-0.1°), but these would have a negligible impact on network performance, thus degrading convergence speed.

Nonetheless, there is no analytical proof that the above method does not get trapped in a local minimum. For this reason, the proposed algorithm has to be compared with a state-of-the-art metaheuristic designed to find the globally optimal solution (e.g., Taguchi method). Simulation results presented next will show that the proposed method finds solutions as good as Taguchi, but with much less computational effort.

VI. PERFORMANCE ASSESSMENT

This section presents the simulations performed to assess the proposed algorithm. The simulation set-up is described first and results are discussed later.

A. SIMULATION SET-UP

Performance assessment is carried out with a grid-based static system-level simulator implemented in Matlab [47]. Table 1 presents the main parameters of the tool.

A realistic scenario is implemented in the simulator, consisting of 129 macro LTE cells of a downtown area of 150 km^2 in a big coastal city. The propagation model consists of a classical pathloss and slow fading model. The link layer is modeled with mapping curves obtained from a link-level simulator [55]. For these curves, it is assumed that system bandwidth is 10 MHz, antenna configuration is MIMO 2x2 (typical for downlink) and channel model is Extended Typically Urban 3 km/h. The radio resource management (RRM) model relies on an analytical performance model of the dynamic packet scheduler in base stations, including service differentiation and the consideration of last-TTI transmissions. Such a model is used to compute estimates of user throughput needed for evaluating QoE on a per-location and service basis. Finally, the traffic model reflects the irregular spatial traffic distribution derived from connection statistics and timing advance measurements of a live network [14].

TABLE 1: Simulation parameters

Scenario	Number of sites	44
	Number of cells	129
Propagation Model	Pathloss	COST 231 Hata
	Slow fading	Log-normal
	Std. deviation	8 dB
	Correlation distance	20 m
	Grid Resolution	40 m
	Minimum propagation loss	80 dB
Base station model	EIRP max	46 dBm
	Maximum antenna gain	15 dB
	3-dB vertical beamwidth	9.5, 12, 15 °
	3-dB horizontal beamwidth	65
	Antenna tilt angle	[0, 16] °
	Downlink carrier frequency	734 MHz
Mobile station model	Height	1.5 m
	Maximum antenna gain	0 dB
Link layer model	Adaptive modulation and coding based on average SINR per location	
	Antenna configuration	MIMO 2x2
	System bandwidth	10 MHz
	Channel model	ETU 3 km/h
Radio resource model	No. of physical resource blocks (PRB)	50
	User throughput based on cell load, SINR and last-TTI ratio per service	
Traffic model	Spatial distribution based on cell-level connection statistics and timing advance measurements	
	PRB utilization ratio	[5, 70] %
	Avg. PRB utilization ratio	24 %

TABLE 2: Service performance statistics derived from traces

Name	Social/Web	App download	Video	Total
$N_{conn}(s)$	432128	75593	94406	602127
$V_T^{DL}(s)$ [GB]	5.96	472.04	49.53	528.28
$V_l^{DL}(s)$ [GB]	2.76	72.61	15.69	91.08
$V_l^{DL}/V_T^{DL}(s)$	0.498	0.165	0.340	0.336
$\overline{R_l}(s)$	0.995	0.742	0.935	0.892
$\max_c R_l(c,s)$	0.999	0.965	0.966	0.999

The simulator is adjusted with data from real connection traces. Table 2 summarizes trace statistics, broken down by service, where $N_{conn}(s)$ is the total number of connection for service s, $V_T^{DL}(s)$ is the total volume transmitted in the network for service s in the downlink, $V_l^{DL}(s)$ is the total data volume transmitted in last TTIs for service s in the downlink, and $\overline{R_l}(s)$ is the average time ratio of last TTIs for service s.

Six different self-planning approaches for antenna tilts are compared:

1) OS (Operator Solution): the tilt plan currently implemented by the operator, which is the starting point for the local search methods.
2) HLS (Heuristic Local Research): a heuristic rule-based fuzzy logic controller proposed in [14], modifying tilt angles to improve SINR across the network, driven by indicators reflecting cell overshooting, useless cell overlapping and bad cell-edge coverage on a cell basis. Basically, HLS downtilts antennas with high cell overshooting and useless cell overlapping, and uptilts antennas with bad cell-edge coverage.
3) HLS-CR (HLS Congestion Relief): a variant of the HLS method including a basic congestion relief algorithm. The aim of HLS-CR is to solve localized congestion problems by reducing cell service areas by downtilting antennas while solving cell-edge coverage problems by uptilting antennas. The inputs to the algorithm are Physical Resource Block utilization, PRB_{util}, reflecting cell load in the Physical Downlink Shared Channel (PDSCH), and cell-edge bad coverage ratio, R_{bc}, computed from reference signal level and timing advance statistics on a cell basis. Figure 4 shows the input membership functions, μ, used to map numerical input values to fuzzy qualifiers (LOW, HIGH). Table 3 shows the inference rules. For instance, rule 1 reads as "IF R_{bc} is High in cell c (i.e., bad cell-edge coverage), THEN $\triangle\alpha(c)$ is Negative (i.e., uptilt)". Similarly to HLS, the output is the tilt change rounded to the nearest integer, so that $\triangle\alpha_{HLS,HLS-CR}(c) \in \{-1,0,1\}$.

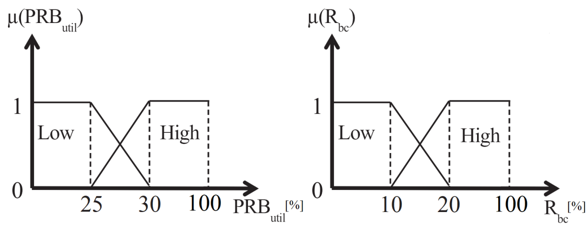


FIGURE 4: Membership functions for CR algorithm.

TABLE 3: Inference rules for CR algorithm.

Rule	$R_{bc}(c)$	$PRB_{util}(c)$	$\triangle\alpha(c)$
1	High	-	Negative
2	-	High	Positive
3	-	Low	Zero
4	Low	-	Zero

4) DC (Decoupled Cells): the first variant of the QoE-driven gradient-based algorithm in this work. This algorithm takes advantage of cell decoupling, where tilt changes are proportional to expected QoE improvements.
5) DC-GS (DC with Gain Scheduling): the second variant of the QoE-driven gradient-based algorithm in this work. This algorithm takes advantage of cell decoupling with gain scheduling.
6) TAG (Taguchi): the Taguchi algorithm for tilt planning proposed in [17], [56], adapted here to consider QoE_{global} as the objective function to maximize. Taguchi algorithm is an iterative method that uses Orthogonal Arrays [57] to systematically define a reduced subset of representative combinations of the decision variables that explore the full solution space. At the end of each iteration, the best solutions found so far are used as center values for the decision variables, defining the new region to explore in the next iteration. Thus, it finds near-optimal solutions in

high-dimensional optimization problems, which is the reason why it is used as a benchmark.

All methods are implemented in Matlab. Different tests are performed in the static simulator. As a proof of concept, the performance of a single iteration of the DC method is first analyzed. The aim of this preliminary analysis is to justify the benefit of grouping decoupled antennas. Then, the above six methods (OS, HLS, HLS-CR, DC, DC-GS and TAG) are compared in the scenario. All iterative methods run until convergence is reached, i.e., when the QoE improvement obtained per iteration is negligible. As a result, the number of iterations is different for each algorithm. The main figures of merit to assess the methods are QoE_{global}, as a network capacity indicator, and $QoE_{user}^{(5th)}$, as a network coverage indicator. Execution times are also shown, but as a secondary figure of merit, since network planning is done offline.

B. RESULTS

A preliminary analysis aims to show the benefit of defining groups of decoupled cells. For this purpose, a single iteration of three basic optimization approaches is executed:

1) In the *individual* approach, every antenna is moved according to the best $\triangle QoE_{cluster}$ prediction, and tilt changes are progressively implemented, i.e., antenna movement for cell 1 is predicted and implemented, cell 2 movement is then predicted (considering the new antenna setting of cell 1) and implemented, and so on. This approach ensures proper network performance evaluations, but requires updating interference matrices N_c times per iteration.
2) In the *simultaneous* approach, every antenna is moved according to the best $QoE_{cluster}$, but tilt changes are not implemented until all cells are analyzed. This option saves network calculations (only one matrix recalculation for the complete analysis), but the prediction of QoE benefit made individually per cell (with only 1 antenna movement) could not match the final network performance at the end of the iteration (with all antenna movements).
3) In the *group* approach, DC algorithm divides the scenario into groups of distant cells that are optimized at the same time. This option can be seen as an intermediate solution between the individual and simultaneous approaches, i.e., cells in a group are modified with the simultaneous approach, but different groups are modified as in the individual method. The aim is to save calculations for cells in the same group, while not losing accuracy in the estimation of QoE benefits.

Figure 5 shows the improvement on the global QoE (in MOS points), $\triangle QoE_{global}$, in a first iteration and for each of the 129 cells of the scenario achieved by the different approaches. The individual approach always gets QoE_{global} improvements (positive values). This result was expected, as its performance predictions are always right, because they are made with the same network settings as when the movement is implemented. At the end of the iteration, the global QoE benefit is $\triangle QoE_{global} = 0.1915$. In contrast, with the simultaneous approach, QoE improvement can be largely negative or positive. This is the result of simultaneously changing all antennas without a proper performance evaluation, resulting in a total negative $\Delta QoE_{global} = -0.5980$ (i.e., the new tilt plan severely degrades network performance). In the group approach, even if some cells slightly degrade their QoE, the overall network performance is improved, with $\Delta QoE_{global} = 0.0393$. The execution time is 32017, 430 and 3759 seconds for the individual, simultaneous and group approaches, respectively. These results show the adequate trade-off between solution quality and computational efficiency in the group approach.

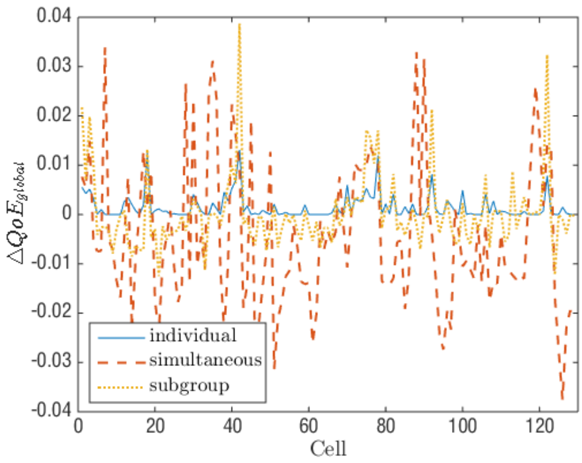


FIGURE 5: Comparison of basic tilt optimization approaches.

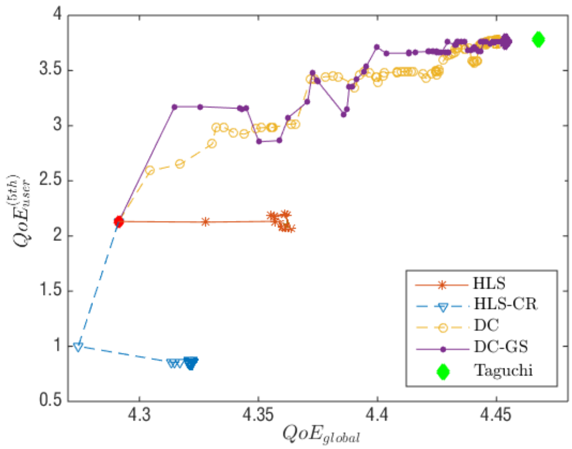


FIGURE 6: Network performance evolution.

After the preliminary analysis, the six planning methods (OS, HLS, HLS-CR, DC, DC-GS and TAG) are compared. Figure 6 shows network performance obtained by the different methods across iterations. Each point represents the proposed solution across iterations, whose coordinates are

TABLE 4: Network performance for different tilt planning approaches.

Algorithm	HLS	HLS-CR	DC	DC-GS	TAG
initial QoE_{global} (OS)			4.29		
initial $QoE_{user}^{(5th)}$ (OS)			2.13		
final QoE_{global}	4.36	4.31	4.45	4.46	4.47
final $QoE_{user}^{(5th)}$	2.11	0.85	3.75	3.76	3.78
QoE_{global} improvement [%]	1.66	0.52	3.70	3.79	4.10
$QoE_{user}^{(5th)}$ improvement [%]	-0.69	-59.81	75.97	76.45	77.51
No. of iterations	25	25	10	10	11000
Runtime per iteration [s]	70	64	4778	4673	164.94
Total runtime [s]	1750	1599	47783	46729	1814400

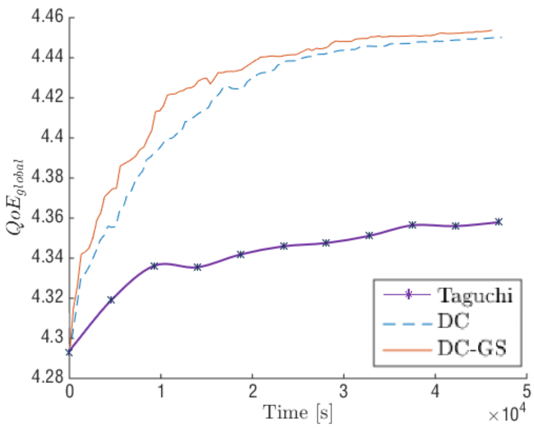


FIGURE 7: Convergence process for the best methods.

the coverage indicator, $QoE_{user}^{(5th)}$, and the capacity indicator, QoE_{global}. Points on the upper right of the figure correspond to better tilt plans. For clarity, the first and last iterations are highlighted with a larger marker. Recall that OS is the initial solution for the other methods, so that network performance at first iteration is identical for all methods. Also note that DC/DC-GS curves include the result from every group change (i.e., they represents steps instead of iterations), so as to show a more detailed evolution of the proposed methods. Table 4 summarizes the main network performance indicators at the end of the optimization process. Initial values (i.e., OS figures) are also included in the Table for comparison reasons. As expected, Taguchi provides the best solution ($QoE_{global} = 4.47$ and $QoE_{user}^{(5th)} = 3.78$), which can be considered as an upper bound for the other methods. HLS manages to improve the global QoE (from 4.29 to 4.36, 1.6%) by increasing the average system SINR by 1 dB without affecting cell edge users (note that $QoE_{user}^{(5th)}$ is only degraded 0.69%). HLS-CR only improves the global QoE slightly (from 4.29 to 4.31, 0.5%) even if cell load in the most congested cells is reduced by up to 20%. Moreover, it severely deteriorates neighbors' cell edge (as $QoE_{user}^{(5th)}$ is more than halved). A close inspection of the trajectory followed by these methods reveals that most of their benefits are obtained in the first iterations. More importantly, neither HLS nor HLS-CR achieve large improvements on global QoE because they do not take QoE explicitly into account. In contrast, the proposed QoE-driven methods, DC and DC-GS, achieve significant performance gains at the end of the iterative process (QoE_{global}=4.45 and 4.46, $QoE_{user}^{(5th)}$=3.75 and 3.76). Both end up with a similar QoE performance, even if they follow different trajectories. However, as shown later, gain scheduling in DC-GS achieves larger performance gains in the first iterations. More importantly, DC and DC-GS find a high-quality solution whose performance is almost identical to the near-optimal solution obtained by Taguchi (QoE_{global}=4.47 and $QoE_{user}^{(5th)}$= 3.78).

Finally, computational efficiency is evaluated. Table 4 breaks down the execution times in a personal computer with a Intel(R) Core(TM) i5-3470 4-core 3.5 GHz CPU with 16 GB of DDR3 RAM. Taguchi achieved the best network performance at the cost of an excessive runtime (1,814,400 s, $\approx$ 21 days). In contrast, DC and DC-GS take much less time (47,783 s for DC and 46,730 s for DC-GS, only 2.6% of Tagughi's time). Note that, even if DC and DC-GS achieve similar network performance at the end of the optimization process, their convergence speed is not similar. Figure 7 compares the evolution of QoE_{global} through time for both algorithms. The convergence speed for DC-GS is higher, so better network results are achieved before. It is also observed how Taguchi reaches significantly lower QoE values in the same amount of time, due to its longer computing time. Not shown in the figure, the same trend is observed with $QoE_{user}^{(5th)}$ evolution.

VII. CONCLUSIONS

Finding the best configuration for antenna tilts is one of the most critical and time consuming tasks for mobile network operators, regardless of the radio access technology. In this work, a computationally efficient method for QoE-driven self-planning of antenna tilts has been presented. The core of the method is the grouping of cells with no mutual interference to speed up the search for the optimal solution with a classical gradient-based algorithm. Simulations results have shown that the two variants of the algorithm reach solutions of extreme quality in much less time than Taguchi algorithm (40 times faster). Thus, runtime is reduced from days to hours.

With legacy approaches, tilt re-planning is only done when system infrastructure is updated (e.g., every time a new site or a new software feature affecting network quality/capacity is deployed). It is also occasionally used to cope with permanent changes in the environment (e.g., new obstacle affecting line of sight or new hot-spot modifying spatial traffic distribution). The availability of a computationally efficient self-planning method as the one presented here makes that tilt re-planning can be done more frequently (e.g., on a weekly instead of on a monthly basis), for different time periods (e.g., different tilts for working days and weekends) and larger geographical areas (e.g., the whole network instead of a cell cluster). Moreover, its ability to evaluate QoE aspects can be used to deal with the launch of new terminals and applications altering the traffic mix and user expectations.

The proposed method is conceived as a centralized solution that can be integrated in a radio network planning tool. A distributed version for evaluating tilts for cells within a group in parallel can also be implemented, but the different groups must still be evaluated sequentially.

REFERENCES

[1] 5G PPP, "5G empowering vertical industrie," February 2016.

[2] V. W. Wong, R. Schober, D. W. K. Ng, and L.-C. Wang, Key technologies for 5G wireless systems. Cambridge University Press, 2017.

[3] J. Ramiro and K. Hamied, Self-organizing networks: self-planning, self-optimization and self-healing for GSM, UMTS and LTE. John Wiley & Sons, 2011.

[4] N. Alliance, "Next generation mobile networks recommendation on SON and O&M requirements," Req. Spec. v1, vol. 23, 2008.

[5] K. Dongwoo, "Downlink power allocation and adjustment for CDMA cellular systems," IEEE Communications Letters, vol. 1, no. 4, pp. 96–98, July 1997.

[6] Kim Dongwoo, "A simple algorithm for adjusting cell-site transmitter power in CDMA cellular systems," IEEE Transactions on Vehicular Technology, vol. 48, no. 4, pp. 1092–1098, July 1999.

[7] T. Cai, G. P. Koudouridis, C. Qvarfordt, J. Johansson, and P. Legg, "Coverage and Capacity Optimization in E-UTRAN Based on Central Coordination and Distributed Gibbs Sampling," in 71st Vehicular Technology Conference. IEEE, May 2010, pp. 1–5.

[8] W. Jianhui and Y. Dongfeng, "Antenna downtilt performance in urban environments," in Military Communications Conference, vol. 3. IEEE, Oct 1996, pp. 739–744 vol.3.

[9] J. Niemelä, T. Isotalo, and J. Lempiäinen, "Optimum antenna downtilt angles for macrocellular WCDMA network," EURASIP Journal on Wireless Communications and Networking, vol. 2005, no. 5, p. 610942, 2005.

[10] O. N. C. Yilmaz, J. Hämäläinen, and S. Hämäläinen, "Self-optimization of remote electrical tilt," in 21st Annual International Symposium on Personal, Indoor and Mobile Radio Communications. IEEE, Sep. 2010, pp. 1128–1132.

[11] I. Luketić, D. Šimunić, and T. Blajić, "Optimization of coverage and capacity of Self-Organizing network in LTE," in 34th International Convention MIPRO. IEEE, 2011, pp. 612–617.

[12] J. Zhang, C. Sun, Y. Yi, and H. Zhuang, "A hybrid framework for capacity and coverage optimization in self-organizing LTE networks," in 24th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications. IEEE, Sep. 2013, pp. 2919–2923.

[13] A. J. Fehske, H. Klessig, J. Voigt, and G. P. Fettweis, "Concurrent Load-Aware Adjustment of User Association and Antenna Tilts in Self-Organizing Radio Networks," IEEE Transactions on Vehicular Technology, vol. 62, no. 5, pp. 1974–1988, Jun 2013.

[14] V. Buenestado, M. Toril, S. Luna-Ramírez, J. M. Ruiz-Avilés, and A. Mendo, "Self-tuning of remote electrical tilts based on call traces for coverage and capacity optimization in LTE," IEEE Transactions on Vehicular Technology, vol. 66, no. 5, pp. 4315–4326, 2017.

[15] U. Turke and M. Koonert, "Advanced site configuration techniques for automatic UMTS radio network design," in 61st Vehicular Technology Conference, vol. 3. IEEE, May 2005, pp. 1960–1964 Vol. 3.

[16] I. Siomina, P. Varbrand, and D. Yuan, "Automated optimization of service coverage and base station antenna configuration in UMTS networks," IEEE Wireless Communications, vol. 13, no. 6, pp. 16–25, 2006.

[17] A. Awada, B. Wegmann, I. Viering, and A. Klein, "Optimizing the radio network parameters of the long term evolution system using Taguchi's method," IEEE Transactions on Vehicular Technology, vol. 60, no. 8, pp. 3825–3839, 2011.

[18] C. W. Chen, P. Chatzimisios, T. Dagiuklas, and L. Atzori, Multimedia quality of experience (QoE): current status and future requirements. John Wiley & Sons, 2015.

[19] J. Mitola, J. Guerci, J. Reed, Y.-D. Yao, Y. Chen, T. C. Clancy, J. Dwyer, H. Li, H. Man, R. McGwier et al., "Accelerating 5G QoE via public-private spectrum sharing," IEEE Communications Magazine, vol. 52, no. 5, pp. 77–85, 2014.

[20] K. Lin, W. Wang, X. Wang, W. Ji, and J. Wan, "QoE-driven spectrum assignment for 5G wireless networks using SDR," IEEE Wireless Communications, vol. 22, no. 6, pp. 48–55, 2015.

[21] A. Imran, A. Zoha, and A. Abu-Dayya, "Challenges in 5G: how to empower SON with big data for enabling 5G," IEEE Network, vol. 28, no. 6, pp. 27–33, Nov 2014.

[22] G. Wilson, "Electrical downtilt through beam-steering versus mechanical downtilt (base station antennas)," in Vehicular Technology Society 42nd VTS Conference - Frontiers of Technology, May 1992, pp. 1–4 vol.1.

[23] D. J. Y. Lee and C. Xu, "Mechanical antenna downtilt and its impact on system design," in 47th Vehicular Technology Conference. Technology in Motion, vol. 2. IEEE, May 1997, pp. 447–451 vol.2.

[24] I. Forkel, A. Kemper, R. Pabst, and R. Hermans, "The effect of electrical and mechanical antenna down-tilting in UMTS networks," in 3rd International Conference on 3G Mobile Communication Technologies, May 2002, pp. 86–90.

[25] J. Niemela and J. Lempiainen, "Impact of mechanical antenna downtilt on performance of WCDMA cellular network," in 59th Vehicular Technology Conference., vol. 4. IEEE, May 2004, pp. 2091–2095 Vol.4.

[26] M. Garcia-Lozano and S. Ruiz, "Effects of downtilting on RRM parameters," in 15th International Symposium on Personal, Indoor and Mobile Radio Communications, vol. 3. IEEE, Sep. 2004, pp. 2166–2170 Vol.3.

[27] F. Gunnarsson, M. N. Johansson, A. Furuskar, M. Lundevall, A. Simonsson, C. Tidestav, and M. Blomgren, "Downtilted Base Station Antennas - A Simulation Model Proposal and Impact on HSPA and LTE Performance," in 68th Vehicular Technology Conference. IEEE, Sep. 2008, pp. 1–5.

[28] H. A. Hakim, H. Eckhardt, and S. Valentin, "Decoupling antenna height and tilt adaptation in large cellular networks," in 8th International Symposium on Wireless Communication Systems, Nov 2011, pp. 11–15.

[29] E. Benner and A. B. Sesay, "Effects of antenna height, antenna gain, and pattern downtilting for cellular mobile radio," IEEE Transactions on Vehicular Technology, vol. 45, no. 2, pp. 217–224, May 1996.

[30] V. Wille, M. Toril, and R. Barco, "Impact of antenna downtilting on network performance in GERAN systems," IEEE Communications Letters, vol. 9, no. 7, pp. 598–600, July 2005.

[31] C. Yanyun, H. Alexis, X. Hui, and Y. Xingxiu, "Coverage and Capacity Optimization for 4G LTE Networks Using Differential Evolution," in 5th International Conference on Cloud Computing and Intelligence Systems. IEEE, Nov 2018, pp. 640–645.

[32] H. M. Elkamchouchi, H. M. Elragal, and M. A. Makar, "Cellular Radio Network Planning using Particle Swarm Optimization," in National Radio Science Conference, March 2007, pp. 1–8.

[33] S. Berger, P. Zanier, M. Soszka, A. Fehske, I. Viering, and G. Fettweis, "What is the advantage of cooperation in self-organizing networks?" in Wireless Days. IFIP, Nov 2013, pp. 1–6.

[34] S. Berger, M. Soszka, A. Fehske, P. Zanier, I. Viering, and G. Fettweis, "Joint throughput and coverage optimization under sparse system knowledge in LTE-A networks," in International Conference on ICT Convergence, Oct 2013, pp. 105–111.

[35] Y. Liu, W. Huangfu, H. Zhang, and K. Long, "An Efficient Stochastic Gradient Descent Algorithm to Maximize the Coverage of Cellular Networks," IEEE Transactions on Wireless Communications, pp. 1–1, 2019.

[36] M. Garcia-Lozano, S. Ruiz, and J. J. Olmos, "UMTS optimum cell load balancing for inhomogeneous traffic patterns," in 60th Vehicular Technology Conference, 2004. VTC2004-Fall. 2004, vol. 2. IEEE, Sep. 2004, pp. 909–913 Vol. 2.

[37] M. N. ul Islam, R. Abou-Jaoude, C. Hartmann, and A. Mitschele-Thiel, "Self-optimization of Antenna Tilt and Pilot Power for dedicated chan-

nels," in 8th International Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks, May 2010, pp. 196–203.

[38] B. Partov, D. J. Leith, and R. Razavi, "Utility Fair Optimization of Antenna Tilt Angles in LTE Networks," IEEE/ACM Transactions on Networking, vol. 23, no. 1, pp. 175–185, Feb 2015.

[39] A. Engels, M. Reyer, X. Xu, R. Mathar, J. Zhang, and H. Zhuang, "Autonomous Self-Optimization of Coverage and Capacity in LTE Cellular Networks," IEEE Transactions on Vehicular Technology, vol. 62, no. 5, pp. 1989–2004, Jun 2013.

[40] H. Klessig, A. Fehske, G. Fettweis, and J. Voigt, "Improving coverage and load conditions through joint adaptation of antenna tilts and cell selection rules in mobile networks," in International Symposium on Wireless Communication Systems, Aug 2012, pp. 21–25.

[41] J. Wu, J. Bigham, P. Jiang, and J. P. Neophytou, "Tilting and Beamshaping for Traffic Load Balancing in WCDMA Network," in European Conference on Wireless Technology, Sep. 2006, pp. 63–66.

[42] R. Razavi, S. Klein, and H. Claussen, "A Fuzzy reinforcement learning approach for self-optimization of coverage in LTE networks," Bell Labs Technical Journal, vol. 15, no. 3, pp. 153–175, Dec 2010.

[43] J. Li, J. Zeng, X. Su, W. Luo, and J. Wang, "Self-optimization of coverage and capacity in LTE networks based on central control and decentralized fuzzy Q-learning," International Journal of Distributed Sensor Networks, vol. 8, no. 8, p. 878595, 2012.

[44] S. Fan, H. Tian, and C. Sengul, "Self-optimization of coverage and capacity based on a fuzzy neural network with cooperative reinforcement learning," EURASIP Journal on Wireless Communications and Networking, vol. 2014, no. 1, p. 57, 2014.

[45] N. Dandanov, H. Al-Shatri, A. Klein, and V. Poulkov, "Dynamic self-optimization of the antenna tilt for best trade-off between coverage and capacity in mobile networks," Wireless Personal Communications, vol. 92, no. 1, pp. 251–278, 2017.

[46] V. Pedras, M. Sousa, P. Vieira, M. P. Queluz, and A. Rodrigues, "Antenna tilt optimization using a novel qoe model based on 3g radio measurements," in 20th International Symposium on Wireless Personal Multimedia Communications, Dec 2017, pp. 124–130.

[47] P. A. Sánchez, S. Luna-Ramírez, C. Gijón, M. Toril, and J. L. Bejarano, "A data-driven scheduler performance model for QoE assessment in a LTE radio network planning tool," Computer Networks, p. 107186, Mar 2020.

[48] ITU-T, "Recommendation p. 800.1: Mean Opinion Score (MOS) terminology," Technical Report, 2006.

[49] J. Á. Fernández-Segovia, S. Luna-Ramírez, M. Toril, A. B. Vallejo-Mora, and C. Úbeda, "A computationally efficient method for self-planning uplink power control parameters in LTE," EURASIP Journal on Wireless Communications and Networking, no. 1, p. 80, 2015.

[50] J. Nocedal and S. J. Wright, Numerical Optimization, 2nd ed. New York, NY, USA: Springer, 2006.

[51] J. Parikh and A. Basu, "Impact of base station antenna height and antenna tilt on performance of LTE systems," IOSR Journal of Electrical and Electronics Engineering, vol. 9, no. 4, pp. 06–11, 2014.

[52] J. Kiefer, J. Wolfowitz et al., "Stochastic estimation of the maximum of a regression function," The Annals of Mathematical Statistics, vol. 23, no. 3, pp. 462–466, 1952.

[53] J. C. Spall, "Multivariate stochastic approximation using a simultaneous perturbation gradient approximation," IEEE Transactions on Automatic Control, vol. 37, no. 3, pp. 332–341, March 1992.

[54] S. Bubeck, "Convex optimization: Algorithms and complexity," Foundations and Trends in Machine Learning, vol. 8, no. 3-4, pp. 231–357, 2015.

[55] C. Mehlführer, J. C. Ikuno, M. Simko, S. Schwarz, M. Wrulich, and M. Rupp, "The Vienna LTE simulators - enabling reproducibility in wireless communications research," EURASIP Journal on Advances in Signal Processing, no. 29, 2011.

[56] A. Awada, B. Wegmann, I. Viering, and A. Klein, "A joint optimization of antenna parameters in a cellular network using Taguchi's method," in 73rd Vehicular Technology Conference. IEEE, 2011, pp. 1–5.

[57] Y.-W. Leung and Y. Wang, "An orthogonal genetic algorithm with quantization for global numerical optimization," IEEE Transactions on Evolutionary computation, vol. 5, no. 1, pp. 41–53, 2001.

PABLO A. SÁNCHEZ ORDÓÑEZ received his B.S. degree in Telecommunication System Engineering from the University of Málaga, Spain, in 2017. Currently, he is working as a researcher at the University of Málaga. His research interests include data analytics, radio resource management and optimization techniques.

SALVADOR LUNA-RAMÍREZ received his M.S. in Telecommunication Engineering and Ph.D. degrees from the University of Málaga, Spain, in 2000 and 2010, respectively. Since 2000, he has been with the department of Communications Engineering, University of Málaga, where he is currently Associate Professor. His research interests include self-optimization of mobile radio access networks and radio resource management.

MATÍAS TORIL received his M.S. in Telecommunication Engineering and Ph.D. degrees from the University of Málaga, Spain, in 1995 and 2007 respectively. Since 1997, he is Lecturer in the Communications Engineering Department, University of Málaga, where he is currently Full Professor. He has co-authored more than 150 publications in leading conferences and journals and 8 patents owned by Nokia and Ericsson. His current research interests include self-organizing networks, radio resource management and data analytics.