i-ETC: ISEL Academic Journal of Electronics,
Telecommunications and Computers
CETC2016 Issue, Vol. 3, n. 1 (2017) ID-12

Self-Optimization of Low Coverage and High Interference in Real 3G/4G Radio Access Networks

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***Abstract*—This paper presents a new single cell multi-objective optimization algorithm based on real Mobile Network Operator (MNO)'s data. The objective is to simultaneously optimize low coverage and high interference areas, through out the adjustment of the antenna tilts. The process is achieved using a specific implementation of a Particle Swarm Optimization (PSO) algorithm. Both the detection of sub-optimal performance areas and its subsequent optimization are supported by real Drive Test (DT) data and MNO network information, which allows its straightforward application in real scenarios. The antenna optimization algorithm was tested in 3^{rd} Generation networks. In this work, a 3G urban scenario is approached, achieving an average optimization gain of 78%, when compared to initial scenario.**

Keywords: Wireless Communications, SON, Self-optimization, Particle Swarm, Antenna Tilt

I. Introduction

The current mobile networks provide service to an all time record of subscribers. The total number of mobile subscriptions in Q1 2017 was around 7.6 billion [1]. The number of subscriptions is expected to keep growing on average 3% year-on-year, mainly due to the developing markets. In order to answer to this demand, the current and beyond mobile networks, must use their resources as efficiently as possible. However, network complexity, is reaching a point such that manual network optimization no longer can be executed efficiently. Hence, Self-Organizing Networks (SON) [2] have been seen as the solution, to automatically manage and optimize a mobile network. With SON, it is possible to optimize complex problems (tilts, power settings, etc), which can be impractical for manual optimization. It can also reduce the Mobile Network Operators (MNO) Operating Expense (OpEx).

Within the SON concept, the procedures can be classified into three different classes: Self-Configuration, Self-Healing and Self-Optimization. The Self-Configuration procedures aim to minimize manual configuration of sites integration, services or features. The Self-Healing methods are triggered by incidental events, such as cell or site failure, and tries to mitigate the effects caused by the loss of coverage and/or capacity. Finally, the Self-Optimization encompasses all methods that optimizes radio resource management parameters, including antenna parameters, power settings, packet scheduling, handover control, etc. The present work, which proposes an automatic optimization of the antenna parameters, is included in the Self-Optimization class of SON networks.

The benefits of an optimal antenna tilt configuration have been established throughout the literature. In [3], the authors proposed an autonomous tilt optimization, attaining gains of 10% in the system spectral efficiency, in Long Term Evolution (LTE) networks. Also, in [4] the authors settled the Signal-to-Interference plus Noise Ratio (SINR) and throughput gains when a proper tilt configuration is in use. Regarding the antenna parameters automatic optimization, this field has been receiving valid contributions using different data sources, as well as addressing different optimization targets [5] [6] [7] [8].

It is noteworthy that many of previous studies' results are established in network simulators and simulation assumptions as [9] and [10]. Here the optimization process is based on real mobile network Radio Frequency (RF) measurements, collected by drive testing. Thus, the proposed work can be directly applied in real optimization scenarios.

Typically, MNOs use Drive Tests (DTs) for network performance evaluation, for benchmark purposes and for network radio link troubleshooting. The DT data is collected using specific hardware which scans the RF spectrum measuring all received cell signals at each location covered by the route of the car conducting the DT. Each cell signal measurement aggregates both the signal strength (Received Signal Code Power (RSCP)) and the signal interference level (Energy to Interference Ratio (E_c/I_0)). So, at each set of geographical coordinates, covered by the DT, it is possible and very common, to have signals from different cells at the exact same location. These RF metrics associated with the respective cells support the proposed methodology in this work. Nonetheless, other data sources containing the same RF metrics can be used, as geopositioned network traces [11].

This work is incremental to [12] and [13] where algorithms for DT quality classification and troubleshooting diagnosis were proposed. This work extends previous work by adding an optimization module, which optimizes the antenna physical parameters to improve network performance. Based on DT data, where it can be detected either low coverage or high interference scenarios, a newly objective function implementation, describes the problem. Furthermore, it was used a Particle Swarm Optimization (PSO) algorithm [14] to find a new antenna configuration, that is optimal or at least minimizes the unintended RF scenario, thus optimizing the low coverage and/or interference scenario.

This paper is organized as follows. Section II describes the algorithm implementation, Section III highlights the obtained results and finally, in Section IV, conclusions are drawn.

II. Cell Multi-objective Optimization

Cell coverage optimization and cell interference mitigation, are generally at two ends of cell optimization procedures. For the first, a new set of antenna physical parameters, that increase the cell coverage area, should fix the low coverage issue. In order to mitigate interference, parameters settings leading to a cell coverage area reduction should be used. The bottom line, is that these are conflicting objectives. On achieving one objective, it may lead missing the other. In such scenarios, a compromise configuration, that minimizes both RF problems is proposed.

The inverse configuration for coverage and interference optimization, is partly explained by the fact that a cell is not an isolated system and neither it should be. It should exist a certain amount of overlap between neighbor cells coverage areas, to allow user mobility. Nonetheless, if excessive, it generates interference and diminishes the network performance. On the opposite, it may lead to coverage holes between cells and cause user drop calls. In fact, coverage and interference optimization, results on the configuration of the antenna physical parameters that gets the right amount of cells overlapped areas.

A. Particle Swarm Optimization

Considering n cells, with p parameters each, to be optimized, the space of admissible solutions grows exponentially with the number of cells considered and respective parameters. Thus, a meta-heuristic algorithm, which is able to find good solutions with limited computational resources and with enhanced performance, as is the PSO [14] was used. The PSO technique makes no assumptions about the problem being optimized and it can search large spaces of solutions. Additionally, it does not require a differentiable optimization cost function, as classic optimization methods require (*i.e.* gradient descent). It is also a population based search algorithm that compared with single solution based algorithms (*i.e.* simulated annealing), allows a greater solution space exploration, leading to better solutions, as in [15], [16]. Furthermore, in [17] the authors compare the performance of the PSO with the Genetic Algorithm (GA) [18] using several benchmark test problems, showing that both reached equally good solutions with less computational effort for the PSO. Hence, the PSO is both efficient and reliable which is appropriate for the antenna tilt optimization problem.

The PSO origins are sociologically inspired, considering that the original algorithm was based on the sociological behavior of the bird flocking. A population of particles, where each particle constitutes a potential solution to the problem, create a swarm s. Each particle i, has associated with it, three different characteristics: the current position of the particle x_i, the current speed of the particle v_i and the personal best position of the particle y_i. In a minimization problem, as the cell multi-objective optimization, the smaller the function value is, the higher fitness it has.

The objective function that is being minimized is denoted by the symbol f. Being an iterative algorithm, at each iteration, the personal best position is updated according to (1),

$$y_i(t+1) = \begin{cases} y_i(t) & \text{if} \quad f(x_i(t+1)) \geq f(y_i(t)) \\ x_i(t+1) & \text{if} \quad f(x_i(t+1)) < f(y_i(t)) \end{cases} \tag{1}$$

with dependence on the time step t.

The PSO $gbest$ model was used. This model maintains a single best solution $\hat{y}$, which is the best position discovered by any of the particles until the t instant.

In Figure 1, the position and speed vector of all particles x_i composing a swarm s in two different iterations are presented. The optimal solution is $(x_1, x_2) = (0, 0)$ and the red dot at each time instant is the global best position $\hat{y}$.

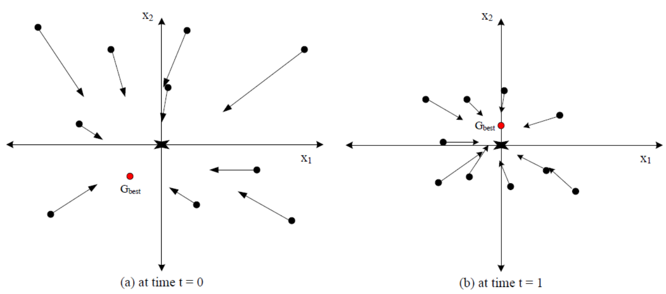

Fig. 1. Speed and position updated for a particle [19].

When time $t = 0$ the swarm particles are considerably dispersed but tending to converge to the $\hat{y}$ position. Meanwhile, the next iteration attempts to reach the previous global best position discovering a new $\hat{y}$. The latest $\hat{y}$ position is closer to the optimal solution and the swarm is converging for the new global best position. A few more iterations and eventually the swarm will converge to the optimal solution.

Finally, the algorithm is executed until the stopping criteria is fulfilled. About the stopping criteria, there are several options. One of the most common approaches is to execute the algorithm until a fixed number of iterations is reached. However, other criteria such as checking if all particles have stopped, is also valid.

Overall the algorithm works as follows: initially, one particle is identified as the best particle due to its fitness value. Then, all the other particles are accelerated towards it, but also in the direction of their best solutions that have been discovered previously. Occasionally, the particles will overshoot their target and consequently explore the search space surrounding the currently best particles. Since most objective functions have some continuity, the probability of having a good solution surrounded by equally good, or better solutions, is high. By approaching the currently best solution from several directions, chances are good, since these neighboring solutions will be discovered by one of the swarm particles.

B. Optimization Targets

The optimization process aims to reduce coverage holes, overshooting and pilot pollution scenarios, by proposing new antenna tilt configurations, that best trade-off coverage and interference. Hence, the development of a methodology that quantifies the extent of the severity of any coverage hole, overshooting and pilot pollution scenario is mandatory. From now on, when referring to all the collected DT signal measurements from a specific cell, we will refer as the cell's footprint. From previous work [12], it is possible to analyze a cell's footprint and to identify which DT measurements correspond to any of the above mentioned RF scenarios. Moreover, also in [12], these portions of the cell's footprint are grouped into clusters, considering their geographical position, as opposed to be treated individually. In Figure 2, an example of DT data cluster division is showed.

Fig. 2. Example of DT measurements division in clusters.

Each circle identifies a DT data measurement and its color is attributed accordingly to its respective cluster. It can be seen that the cluster arrangement depends on the relative distances between each DT data measurement.

After the described process, the clusters are evaluated by an objective function, with respect to a specific optimization target, $C_{target}(\Omega)$ given by,

$$C_{target}(\Omega) = \beta_1 \sum_{c=1}^{k} \left(\frac{b_c}{B} \times H_{target}(c) \right) + \beta_2 \frac{k}{T}, \quad (2)$$

where Ω represents the set of antenna adjustable parameter values, with respect to the considered DT, k is the number of clusters in which the optimization target was identified, b_c is the number of measurements in the cluster c, B is the total number of the target clusters measurements and $H_{target}(c)$ is the target cluster severity that classifies the performance degradation in cluster c. T is the total number of clusters that compose the cell's footprint. β_1 and β_2 are configurable to optimize based on the number of the detected clusters or its severity for the network. The $H_{target}(c)$ evaluates a cluster c for the magnitude of a given target (*i.e.* coverage holes, overshooting or pilot pollution) severity. It takes values between zero and one, where zero indicates the absence of the considered target and one is the maximum possible influence of the given target. Also, $C_{target}(\Omega)$ takes values between zero and one, as long as, $\beta_1 + \beta_2 = 1$, is verified. Again, the optimal outcome is zero, which indicates that there are no clusters where the optimization target was identified.

Given a cell's footprint, with clusters where coverage holes, overshooting and pilot pollution were identified, these are evaluated independently by the respective objective functions $C_{CH}(\Omega)$, $C_{OS}(\Omega)$, $C_{PP}(\Omega)$. These functions consider the respective target clusters and evaluate them using (2) with the corresponding severity cluster functions (*i.e.* $H_{CH}(c)$, $H_{OS}(c)$ and $H_{PP}(c)$). These functions are detailed in [12].

The key point is that each optimization target (optimization of coverage holes, overshooting or pilot pollution scenarios), is classified individually and the objective is to optimize them in group. Thus, the PSO algorithm minimizes a linear combination of the individual objective functions, given by,

$$C(\Omega) = \alpha_1 C_{CH}(\Omega) + \alpha_2 C_{OS}(\Omega) + \alpha_3 C_{PP}(\Omega), \quad (3)$$

where C_{CH}, C_{OS}, C_{PP} are the individual objective function for coverage holes, overshooting and pilot pollution targets, respectively. α_1, α_2 and α_3 are the respective optimization weights allowing to prioritize any target, for situations where an optimal solution is not feasible.

The PSO will propose new configurations Ω and evaluate their fitness or performance by calculating the value of $C(\Omega)$. The objective is to find the configuration Ω that minimizes $C(\Omega)$, achieving the configuration that provides the best performance for a given cell.

Reflecting the concern of possibly diminishing the neighbor cells performance by optimizing one cell, and the fact that it was common to identify multiple antenna configurations that minimize to zero the objective function, a secondary objective function, $M(\Omega)$, was added. It aims to provide a single solution to any cell optimization scenario and to minimize performance degradation in the neighbor cells, by optimizing the parameters of one cell. This secondary function is only minimized if the primary objective function is totally minimized ($C(\Omega) = 0$). In fact, a new global objective function is introduced,

$$G(\Omega) = C(\Omega) + M(\Omega) + 0.5 \quad (4)$$

where $C(\Omega)$ is given by (3) and $M(\Omega)$ is given by,

$$M(\Omega) = \begin{cases} -\left(0.5 - \frac{\sum_{p=1}^{j}(|\Omega_p - A_j|)}{2\sum_{p=1}^{j}(\Delta_j)}\right) &, \quad C(\Omega) = 0 \\ 0 &, \quad C(\Omega) > 0 \end{cases} \quad (5)$$

where j is an antenna adjustable parameter value, from the current configuration Ω, A_j is the original antenna parameter value and Δ_j is the maximum value difference, from the antenna original configuration, that a new configuration can obtain. The bottom line, is that the cell optimization algorithm should minimize the objective targets and return an antenna configuration that is as close as possible to the original antenna configuration. This condition is evaluated by $M(\Omega) \in [-0.5, 0]$, where -0.5 represents a configuration equal to the original configuration. The key point is that it acts as a similarity measurement to the original antenna configuration, and a new configuration will be preferred as much as its similarity to the original configuration.

C. Antenna Physical Parameters

In this section, the relationship between the considered antenna physical parameters, the optimization targets and the PSO algorithm is explained. Moreover, it were considered the Mechanical Downtilt (MDT) and Electrical Downtilt (EDT) as the possible antenna optimization parameters. In Figure 3, the overall flowchart of the proposed antenna optimization solution is presented.

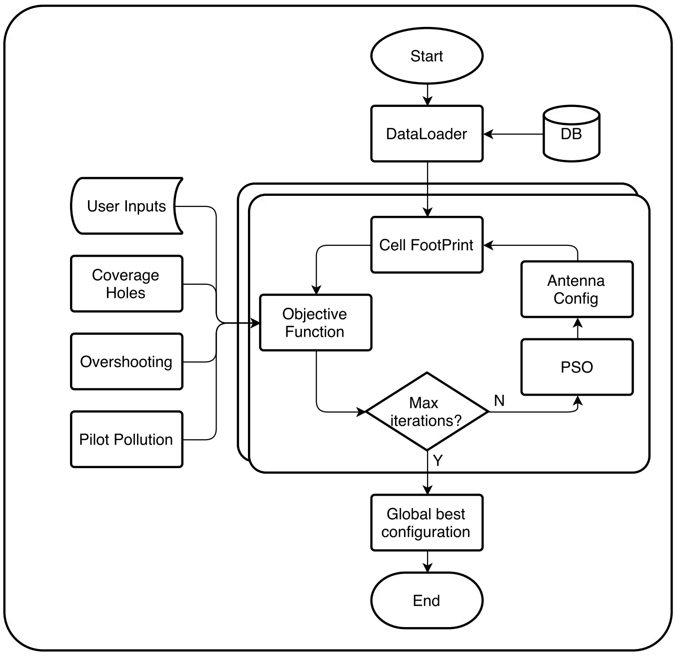

Fig. 3. Antenna optimization algorithm.

The first block is the data loader. This module retrieves the network topology, consisting on the surrounding sites location, as well as the respective cell logical information and antenna characterization. Also, all DT data relevant for the cell being optimized, is loaded. Thus, the cells complete footprint is gathered from a database. The fetched DT measurements are divided into clusters, which enables to detect areas with prevailing RF behaviors and not simply variations due to the radio channel fading and multipath, as it might happen in case of an individual DT measurement analysis. The cluster division, based on [12], is achieved using an agglomerative hierarchical clustering algorithm. Figure 4 presents a generic example of a tree structure called dendrogram, which is the result of the application of an agglomerative hierarchical clustering algorithm to a dataset with 10 data entries.

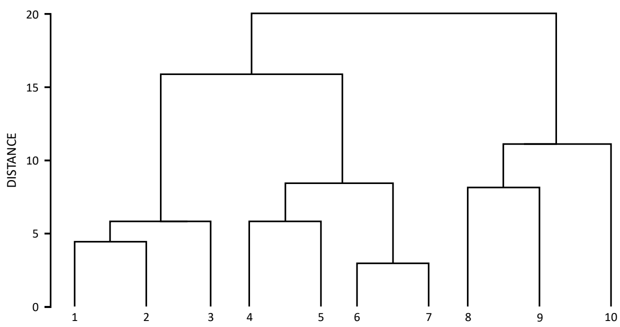

Fig. 4. Dendrogram tree structure.

In the context of this work, the objective is to group a set of DT measurements into clusters. The agglomerative hierarchical clustering algorithm, initially considers each DT measurement as a cluster. Iteratively, merges the two closest clusters, using a similarity criteria based on distance, until all the DT measurements constitute a single cluster, thus creating a dendrogram structure (see Figure 4). Then, considering a cluster maximum size, which is defined by the user, the cluster division, with less clusters is chosen. It provides the cluster arrangement with the biggest cluster sizes within the user defined maximum size.

With the clusters identified, two criteria were applied setting which optimization target it should be evaluated for: the cluster location and the cluster cell dominance. Based on [12], a theoretical cell service area is extrapolated from the cell surrounding topology density. Only clusters beyond this area, are in possible overshooting conditions, and thus only these are considered for the overshooting objective function.

For any given cluster, a given cell could be a dominant, a co-dominant or a non-dominant server [12]. For the purpose of this work, a cell is considered dominant, if it accounts with at least 50% of the serving DT measurements, in that area. A serving measurement is considered the measurement with the highest received power or any measurement with a maximum offset value equal to the soft handover threshold, regarding the best received signal, at each location. A cell is co-dominant if there is at least one other cell to account 50% of the serving measurements. Consequently, any non compliant cell with the above criteria, is a non-dominant cell.

For the coverage holes optimization target, as this problem occurs only within a cell service area, only the cluster areas where the cell is a dominant or co-dominant server, are evaluated by the coverage holes objective function. In the pilot pollution case, as this behavior occurs outside the cell service area, only the clusters where the cell being optimized is a non-dominant server are evaluated by the pilot pollution objective function.

The objective function module (see Figure 3) evaluates the available DT cell footprint taking into account the optimization targets such as coverage holes, overshooting and/or pilot pollution. In this work, the objective function was implemented accordingly to (4). Moreover, the user can customize some parameters, such as the antenna physical parameters that should be optimized as well as some parameters of the PSO algorithm (See Table I).

TABLE I
CELL OPTIMIZATION PARAMETERS.

	Parameter	Description
Antenna Physical Parameters	MDT [°] EDT [°]	Selection of the configuration parameters
Optimization	Coverage Holes Overshooting Pilot Pollution	Selection of the optimization targets
	Service Area Control	Enables service area size extension or reduction
PSO Algorithm	Iterations Particles	Controls the number of particles and iterations

The cell optimization algorithm can optimize one or all the three optimization targets. Besides, two new options allow to, in consequence of a new antenna configuration, to control if the cell service area could or not increase/decrease. The decrease option is only applied to clusters in which there is absence of cell dominance. Clusters where the cell being optimized is dominant, an antenna configuration that undermines the cell dominance, is not allowed.

Regarding the PSO algorithm, two variables are user configurable. The first one, the maximum number of iterations, it should be chosen bearing in mind that with a higher number, the algorithm convergence probability is also higher, but at the expenditure of delayed processing time. The second, the number of initial particles, it should be set, as the previous parameter, balancing execution time and convergence probability.

As stated before, a PSO algorithm is composed by several particles. While the algorithm does not reach the maximum number of iterations, each particle will identify a new antenna configuration, driven by the objective function value. This behavior is illustrated in Figure 3.

The adjustment of any of the antenna parameters above-mentioned, will lead to an antenna gain variation. For a given location, a gain variation in the transmitter, results in the same variation in terms of the received power, as in (6),

$$P_r = P_t - L_t + G_t - L_{Path} + G_r, \tag{6}$$

where P_r is the received power in dBm, P_t is the transmitter power in dBm, L_t is the transmitter power losses in dB, G_t is the transmitter antenna gain in dB, L_{Path} is the path loss in dB and G_r is the receiver antenna gain in dB. As a new antenna configuration only affects the transmitter antenna gain, G_t, and all the other terms of (6) remain constant, the RSCP values that would be received by a terminal equipment are directly estimated.

Regarding the antenna gain variation, it can be estimated either through a theoretical antenna radiation pattern model or using the real antenna pattern. In this work, the theoretical 3^{rd} Generation Partnership Project (3GPP) antenna model [20] was considered.

When the maximum number of iterations is reached, the global best configuration, which is the best configuration, found by any of the PSO particles, is returned.

Overall, each PSO particle position identifies a different antenna configuration. In order to evaluate the fitness of the solution, all the measurements of the cell footprint are updated with the new correspondent power values, due to the different transmitter gain. Then, each cluster is evaluated in terms of coverage holes, overshooting and pilot pollution. As a consequence, the global objective function translates for all footprint clusters the presence and magnitude of any of the above-mentioned RF issues. This way, the algorithm achieves a configuration that minimizes the initial problems without causing new RF performance issues in other clusters that initially had no performance issues.

III. RESULTS

The algorithm was tested in urban and suburban scenarios with real 3^{rd} Generation (3G) data from a mobile operator. For this section, a 3G urban scenario is presented where 14 cells were identified with either coverage, overshooting or pilot pollution issues. Moreover, the PSO was set with 10 particles and a maximum of 100 iterations.

A. Overview

All 14 cases, were optimized taking equally into account, the 3 optimization targets above-mentioned. Taking into account that a gain of 100% represents an antenna configuration that minimizes the objective function to zero, the average gain, for the optimized cells, was 78%, as reported in Table II.

TABLE II
CELL OPTIMIZATION GAIN RESULTS.

	Gain
Average [%]	78
Max [%]	100
Min [%]	0
Standard deviation [%]	34

Moreover, in some cases the attained gain was 100%, meaning that the simulation of the new tilt configuration did not yielded any RF problem. The gain standard deviation presented a high value, nonetheless it is balanced by the high average gain of 78%. Figure 5 presents a comparison between the obtained objective function values, by each cell, before and after optimization. The blue bar represents the objective function value, for each cell, before optimization. Regarding the orange bar, it indicates the objective function after the cell optimization. It can be ascertained that the objective function values, which defines the low coverage and interference severity, are reduced in the majority of the cases

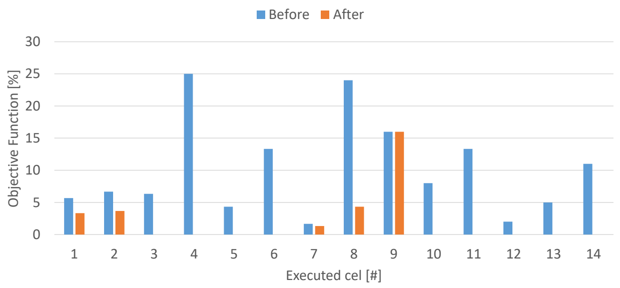

Fig. 5. Comparison of cell optimization results.

to values close to zero, representing the optimal scenario. Equally, it was verified that in 64% of the optimized cells, the objective function was minimized to zero. Interestingly, the optimization of the cell number 9, did not improve the cell performance. After a more detailed analysis it was verified that the cell's footprint was poor in quantity. In such scenario the algorithm could not identify a better trade-off between coverage and interference.

Regarding the optimized cells, these have been manually optimized by radio engineers throughout the cell's life cycle. Nonetheless, as it was done by different radio engineers and with possible different considerations, some optimization actions might have been more effective than others. Hence, some additional variability in the obtained cell optimization gains may be verified. While in some cells it was possible to fully optimize the cell performance, in others the performance was improved, but not optimally.

B. Detailed cell analysis

In this section, a more in-depth analysis of one of the fourteen optimized cells is presented. In Figure 6, the cell (blue), to be optimized, and its footprint are represented. The clusters highlighted with the green color, identify the areas where the blue is a dominant/co-dominant server. The remaining, identify areas that despite the cell reaching it, the cell is not a dominant server.

In this scenario, two clusters of DT measurements were identified with overshooting and pilot pollution optimization problems. The respective $H_{OS}(c)$ and $H_{PP}(c)$ values, for each cluster, which indicate the severity of the problems, are depicted in Figure 6. These metrics are used to calculate respectively, $C_{OS}(\Omega)$ and $C_{PP}(\Omega)$, using (2) and then with (4), the overall cell performance is calculated. Afterwards, the self-optimization algorithm was executed and proposed a new antenna configuration, presented in Table III.

The original antenna configuration was set to three degrees of EDT and two degrees of MDT. The self-optimization algorithm proposed an antenna configuration with five degrees of EDT and seven for the MDT, as reported in Table III.

The new antenna physical configuration increased both the MDT and the EDT, thus optimizing the cell. The applied down-tilt reduced the received power in the initial problematic clusters, nonetheless it did not compromised the own cell service area in coverage matters.

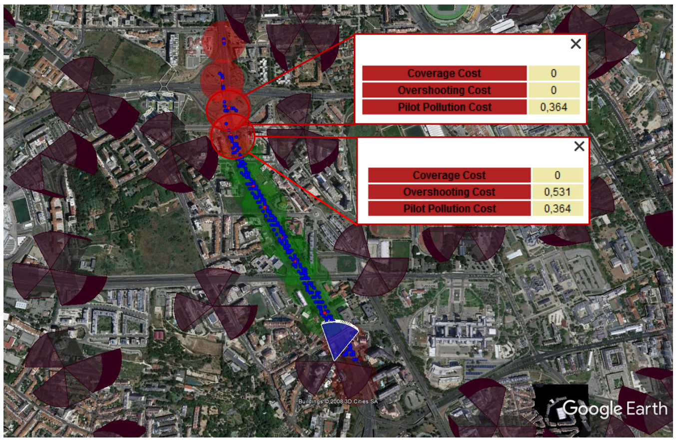

Fig. 6. Cell footprint before optimization.

TABLE III
ANTENNA CONFIGURATIONS COMPARISON.

	Before Optimization	After Optimization
EDT [°]	3	5
MDT [°]	2	7
C(Ω) [%]	5	0

The cell footprint measurements were estimated based on the new transmitter gain and illustrated in Figure 7.

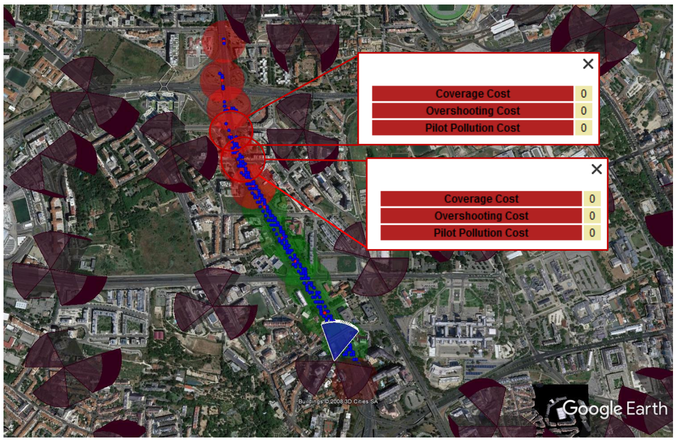

Fig. 7. Cell footprint after optimization.

Firstly, it can be verified that the problematic clusters no longer exhibit neither overshooting nor pilot pollution. Secondly, this new antenna parameter configuration, diminishes the cell service area. This reduction does not impact network coverage, as the two clusters that previously belonged to the cell service area, corresponded to areas of cell co-dominance. This means that other cells reaching those clusters in RF conditions to provide service exist and the reduction of the cell service area does not impact negatively the network performance.

The cell optimization essentially deals with the trade off between maintaining good coverage in the cell service area while diminishing interference in other cell service areas. An antenna physical parameter configuration that minimizes interference is only valid in case of being able to maintain coverage in the own cell service area. In that sense, Figure 8 shows the Cumulative Distribution Function (CDF) of the optimized cell power measurements before and after the optimization in the cell service area.

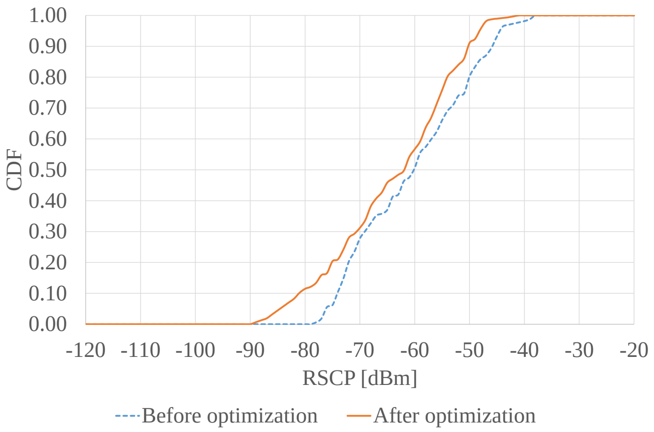

Fig. 8. Received power CDF in the cell service area.

As shown, the power CDF before and after optimization, are similar, which asserts that the new antenna configuration did not degraded the RF conditions in the cell service area. Analyzing more in depth Figure 8, it can be seen that the CDF after optimization reveals slightly lower power magnitude, nonetheless the new values still provide good coverage.

For the power CDF of the cell DT measurements located outside the cell service area, ideally they should have low power values. Figure 9 exhibits the CDF of the cell DT measurements located outside the cell service area, before and after the optimization.

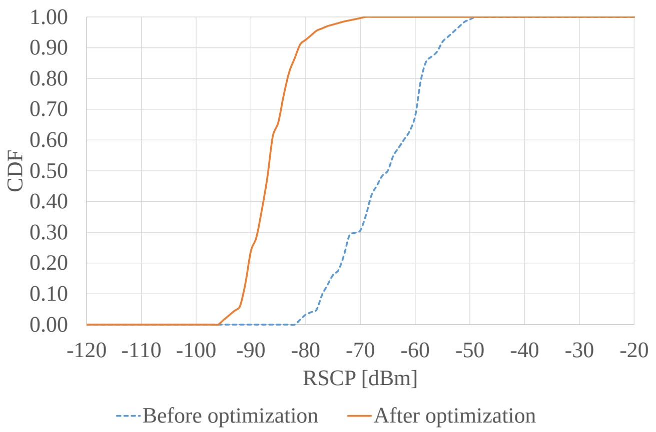

Fig. 9. Received power CDF outside the cell service area.

While the 50% percentile of the power CDF before optimization was around -65 dBm, the equivalent 50% percentile after optimization was around -85 dBm, which stands for a reduction of 20 dB. This magnitude reduction allowed to correct the interference issues of this cell.

Comparing the power CDF of the service area and the surrounding areas, it confirms that the power received outside the service area was reduced significantly, at the expense of a small power reduction in the cell service area. This shows a good trade-off on the overall network performance.

In [6], the authors used a GA to optimize the antenna physical parameters, based on DT measurements. Their results indicated also that it was possible to attain a CDF RSCP curve shift of the same magnitude as the one represented in Figure 9.

Even though, the usage of DT data makes it easy to predict the cell RF metrics for different antenna configurations, it also leads to an important drawback. It can only predict for the areas where the DT covered and collected measurements. On an automatic optimization feature based on this self-optimization algorithm, the extension and quality of the DT should be validated previously to the optimization process using a DT reliability model [13], to ensure that the cell being optimized contains enough DT data. This way, the optimized configuration, would take into account more data, and propose a more reliable configuration.

In alternative, the usage of trace [11] data, has an important advantage. Each iteration of a SON self-optimization feature, which consists on detecting RF performance issues and optimizing it through adjustment of the antenna physical parameters is limited by the time-span between acquiring new data. While using DT data, the time-span can be several days, by using trace data, the time resolution can be as small as fifteen minutes. This enables almost a real time monitoring and optimization of the network.

IV. Conclusions

This paper introduces a single cell multi-objective antenna physical parameters optimization algorithm. Based on DT measurements, the algorithm optimizes coverage and interference levels by proposing optimum tilt values. It optimizes the antenna physical parameters using a custom PSO algorithm.

For the 3G urban scenario, the algorithm optimized the suboptimal performance cells with an average gain of 78%. Also, in 64% of the cases, the new antenna configuration amended all coverage and interference issues.

As the proposed methodology and algorithm can be extended to 4^{th} Generation (4G) network data, with minor changes, work is in motion to evaluate the impact of antenna tilt optimization in 4G networks.

As it is not possible to fully optimize some RF scenarios, by only optimizing one cell, future work will be multi-cell optimization.

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