Interference Detection and Reduction in 3G/4G Wireless Access Network

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Abstract— **For the past few years, mobile communication networks have been through several changes, not only in what concerns to technology level and techniques, but also regarding to planning. Nowadays, telco operators are faced with the need to develop methods to conduct tasks autonomously such as planning, implementation and networks maintenance. In order to overcome some of these challenges, this study focuses on the development of a tool that is able to conduct the process of optimizing the coverage and reducing interferences intra-RAT (Radio Access Technology) autonomously, applying concepts from the Self-Organizing Networks (SON) methodologies. This study is based on the 3rd generation technology from the Universal Mobile Telecommunications System (UMTS). The antenna tilt is considered the most beneficial parameter for the dynamic adjust of the coverage area from the study environments. Through its accurate parametrization it is possible to maximize the areas with good coverage levels and avoid the cells overlapping. The main advantage is the resources management, which is possible by the usage of RET (Remote Electrical Tilt), by allowing the remote adjustment of antenna tilt.**

The simulation tool, with the graphical component in a MatLab® environment, uses a genetic algorithm to find the accurate parametrization of the tilt configuration in the multiple antennas, simultaneously. This algorithm uses as input parameters the network topology and network estimations given by a Drive Test. In order to validate the algorithm of network optimization and interference reduction, three scenarios have been developed. The first uses only a base station. The second counts with multiple antennas, simulating the network performance after changing the possible combinations of the electrical tilt. The last scenario has multiple base stations in which is possible to change the electrical and mechanical tilt values. All of them are based on the measurements made in an urban area in the Lisbon city center. After applying the algorithm, a significant improvement in the Received Signal Code Power (RSCP) level and received energy per chip divided by the power density in the band (Ec/No) was noticed, increasing the average coverage level and reducing the signal degradation in the selected area. In a final stage, the results are exported to the Google™ Earth platform through the tool that was developed.

Index Terms - Self-Organizing Networks, UMTS, Optimization, Coverage, Interference, Genetic Algorithm.

I. Introduction

By the end of the 90s, the Universal Mobile Telecommunications System (UMTS) appears, setting the entrance in the 3rd generation of mobile networks (3G). Defined by the 3rd Generation Partnership Project (3GPP), its goal is to overcome the limitations that, until then, were imposed by the 2nd Generation (2G) systems, Global System for Mobile Communications (GSM). One of the biggest impeller factors for the development of this technology was the fact that there was a great need of higher transmission rates to satisfy the rising search of data services in mobility scenarios. In this way, 3G networks have appeared with the goal to satisfy the following requirements. Firstly, to make available transmission rates until 2Mbit/s per mobile user. Secondly, to make possible data transportation in Packet Switching (PS) mode with Quality of Service (QoS) [1]. Then, to universal use. Finally, to support a bigger diversity of application and access to new contents with a better QoS. The greatest news of this technology is the technique to radio access used, the Wideband Code Division Multiple Access (WCDMA). This makes it a broadband technology of multiple access by code division, opposite to the methods used by the previous generation, which uses TDMA and FDMA technologies. The radio transmission procedure in UMTS consists on the following: in the moment when a connection is made, the signal is modified (modulated) by multiplying itself by a code. This code is constituted by a bit sequence, named as chip, with bit values '0' or '1' that spread the information through the frequency spectrum. To this chip sequence is given the code name of Channelization. One of the advantages of using this technique is the processing gain given by the signal power reduction. Afterwards, the signal is modified, it is transmitted by the transmission channel with a certain frequency, together with the signals from the other users. The sum of the signals cannot surpass the power allowed in the channel. The procedure finishes when the information arrives to the receiver where, based in the Channelization code, it identifies, decodes (despreading) and recovers the base band signal without interfering with the other users' signal.

Nowadays, there are two tasks that need a high attention from the mobile network operators, radio network planning and optimization. With the increase in complexity of the radio networks, these automatization processes have been gaining importance in the past few years, as they are extremely complex when approached manually [2]. Therefore, there is a rise in the will to develop some mechanisms that are able to auto optimize some network parameters in an efficient way, based on Self-organizing network (SON) techniques. In this way, with the need to improve the pace of analysis and the answer to problem resolution, several algorithms were developed, allowing the cost reduction by operators in the network development and updating, as well as in the reduction of human intervention.

The current paper is focused on optimizing parameters in a 3G mobile network, with the objective to solve problems of weak signal level and consequents coverage holes, without affecting the average signal level on the study's area or without creating interference in adjacent cells. In order to accomplish it, an algorithm was developed to assist the coverage optimization process and interference minimization, by changing the tilt of the antenna.

The network performance is studied, by changing only the antenna's electrical tilt, with the goal to be a fast optimization process, which avoids site visits and work force costs, thanks to its trait of remote accessibility. The network behavior is also evaluated when the best antenna's configuration is seek, by giving the chance to modify either the electrical as the mechanical tilt. It is intended to compare the results achieved between both solutions, to understand whether the network performance could be maximized by doing only a remote change of the antennas' inclination angle.

II. Self-organizing network

The SON networks were introduced by 3GPP as part of the LTE (Long Term Evolution) system. These networks are seen as key tools for the improvement of the mobile network operations [3, 4]. Even though this concept has appeared with LTE (known as 4th Generation), this is a generic concept and independent from the technology. Therefore, it is suitable to be implemented in the different mobile generations and each of them can benefit from its features to improve the network performance. At the same time, it helps operators to reduce some costs, specifically human resources investments [5].

SON are defined as a communication network that executes autonomously a set of functions, decreasing human intervention. Usually, this set of functions are executed cyclically, going from data collection to data processing and ending with a method/optimization algorithm [6].

SON techniques aim to acquire enough autonomy to evaluate the network parameters, changing its configuration every time they detect a failure.

A. Coverage and Capacity Optimization

The Coverage and Capacity Optimization (CCO) concept has been receiving great attention due to its extreme complexity. Traditionally, this type of optimization is done based on measures (Drive Tests) and planning tools such as theoretical propagation models. There are countless considerations to be taken into account for the CCO, such as traffic patterns, number of users connected to the network, changes in the physical environment and changes in the service usage [7, 8].

The auto optimization process can be seen as the automatic search for the most suitable values of the several parameters in the network configuration. In a real network, numerous antennas can be installed and functioning in an area. Therefore, the search task may require a high effort, cost and time, due to the multiplicity of possible configuration combinations (as is the example of combinations between antenna tilt, azimuth angles and pilot power transferred). Still, due to the cells coupling, the changes that are made in a cell may influence the observed performance in the area of the adjacent cells. Thus, the use of auto optimization algorithms is needed, as it is extremely hard for an engineer to deal manually with that complexity level.

In the 3G network optimization process, there are two different aspects that can be distinguished. The first is RF (Radio Frequency) optimization, in which the goal is to guarantee the required coverage, avoiding overlap and overshooting problems. The second is optimizing service parameters, including setting of admission and congestion control thresholds, handover limits and maximum downlink power per connection. The first approach is the one that better optimizes the capacity and coverage, as it causes a direct influence in the antenna's radiation diagram, and controls the cell limits without changing the signal noise relation.

Another factor that impelled the choice for RF parameters was the development of the Remote Electrical Tilt (RET) adjustment. RET is seen as one of the main tools for the System optimization as, by allowing to handle remotely, it guarantees great advantages to the mobile operators. The OPEX costs are a big part of a company's costs and, with the usage of RET, it would be possible to reduce dislocation and work force costs. Moreover, it is possible a real time adaptation by doing an automatic, continuous and cyclical antenna tilt, with the goal to improve the network performance in what concerns to coverage and capacity.

B. Antenna Tilt

Tilt is the angle between the horizontal plan and the direction of the main lobe of antenna's radiation pattern. This parameter can be adjusted in two different ways, electrically or mechanically, as represented on the figure 1:

- Mechanical: does not change the entrance signal's phase, therefore, it does not change evenly the entire sector's coverage area. There are two main disadvantages by using this type of tilt. Primarily, its adjustment has to be done in the site, involving operational costs. Also because the main lobe of the antenna bows in the ground's direction, the projection of the opposite lobes happens above the horizon line, which can cause overshooting;
- Electrical tilt: the changes caused induce shifts in the signal phase. Hence, the diagram changes evenly in the 360º, amplifying or reducing equally the coverage area. This tilt can be changed remotely [9].

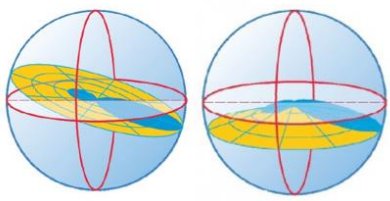

Fig. 1. Differences between mechanical and electrical tilt.

III. Coverage and interference reduction optimization algorithm

The optimization process, illustrated in figure 2, summarizes the steps developed in this work. The procedure consists of a cycle that interacts with the network, causing small changes to the parameters of its configuration and evaluating its performance after each modification.

The cyclic process aims to return a new configuration that simultaneously respects the proposed objectives, quantified in the figure as M. The optimization plan structure defined in this work is divided into different stages. The first refers to available Drive Test's observation. The next phase is the planning process, where it is defined the network performance criteria to be obtained at the end of the process

and to analyze the various methods/ algorithms, that can be used as optimization tools. After, a simulation tool is developed to seek the results required by the operator through the available inputs and implemented algorithm. Network performance evaluations are performed in each configuration change. It is on this stage where the optimization objectives are applied through evaluation functions.

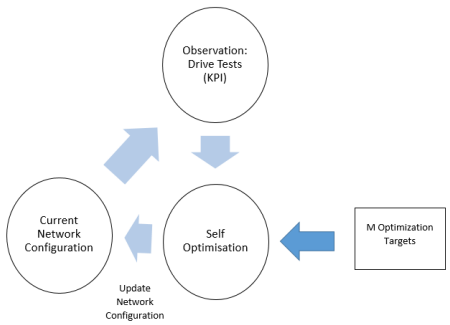

Fig.2. Network self-optimization loop.

A. Key Performance Indicator

In mobile networks there are key performance indicators (KPIs) that play a key role on the system evaluation. The KPI values are obtained through information about the NodeB, obtained through the network controllers (RNC) or Drive Test performing. The latter is the method used to obtain indicators on which the entire optimization process proposed in this work is developed.

These indicators aim to present the information necessary to describe a mobile network and evaluate its performance, both in the planning phase, ensuring the best possible solution, as in the optimization phase, providing real data.

In a downlink(DL) transmission, for coverage verification purposes, the *Received Signal Code Power* (RSCP) in the pilot channel, *Common Pilot Channel Received Signal Code Power* ($CPICH\ RSCP$), and $\frac{Ec}{No}$ (Ratio between the energy per chip (Ec) and the spectral noise density (No)) caused by neighboring cells, in the pilot channel $CPICH$ should be considered. The equations 1, 2 and 3 define these two metrics [10].

$$CPICH\ RSCP\ [dBm] = CPICH\ Power\ [dBm] + G_e[dBi] - A_c[dB] - L_p[dB] \quad (1)$$

$$CPICH\ \frac{Ec}{No}[dB] = \frac{CPICH\ RSCP}{\sum_{1,(n\neq n^*)}^{N^*} CPICH\ RSCP + P_N} \quad (2)$$

$$P_N = \mathrm{k} \times \mathrm{T} \times \mathrm{B} \quad (3)$$

Where:

- G_e: Emission Antenna Gain;
- A_c: Cable Loss;
- L_p: *Path Loss*;
- P_N: *Thermal Noise;*
- k : Boltzmann constant;
- T: Temperature;
- B: Bandwidth;
- N^*: Interfering cells.

Table 1 and 2 show the coverage level and signal quality intervals, respectively, used in the optimization process for the results presentation.

TABLE 1
LEVEL OF CPICH RSCP

Range [dBm]	Definition	
$CPICH\ RSCP$ <= -120	Without Coverage	●
-120 < $CPICH\ RSCP$ <= -100	Weak Coverage	●
-100 < $CPICH\ RSCP$ <= -95	Minimum Coverage	●
-95 < $CPICH\ RSCP$ <= -85	Average Coverage	●
-85 < $CPICH\ RSCP$ <= -75	Good Coverage	●
$CPICH\ RSCP$ > -75	Excellent Coverage	●

TABLE 2
LEVEL OF CPICH EC/NO

Range [dB]	Definition	
$CPICH\ \frac{Ec}{No}$ <= -18	Bad Quality	●
-18 < $CPICH\ \frac{Ec}{No}$ <= -13	Minimum Quality	●
-13 < $CPICH\ \frac{Ec}{No}$ <= -10	Average Quality	●
-10 < $CPICH\ \frac{Ec}{No}$ <= -7	Good Quality	●
$CPICH\ \frac{Ec}{No}$ > -7	Excellent Quality	●

B. Genetic Algorithm

Nowadays, there are algorithms capable of automatize all network planning and optimization process, including the coverage optimization in the SON features.

This study is focused on the development of a tool that is able to deal with real and complex networks, in which is possible to set antennas' setups and make periodical network adjustments. Therefore, the algorithm choice and implementation is a fundamental step of its development. The Genetic Algorithm (GA) has proven to be the one with the best fit to complex problems with multiple elements and solutions [11, 12]. The usage of this type of algorithm has been tested successfully in countless methodologies related to processes of optimization of mobile networks' performance. It is intended that, with the aid of the GA, the simulation tool is able to develop a worthy solution, in an acceptable simulation time, considering a great dimension problem with several variables to take into account. There are two main features that allow it to get these results. The first one, by being a probabilistic algorithm, uses the codification set parameters to optimize, instead of the parameters themselves. In the second, the exploration of the problem's solution is based in a research environment that starts from a population and not from a single point. The GA is an algorithm inspired in the Darwin's Theory of Evolution [13]. It uses the best solutions achieved to find even better propositions. It has mechanisms capable to overcome the local highest, where it benefits from operators able to explore intensively the positive traits of the potential solutions aiming to achieve a set of parameters that maximize the network performance. This algorithm is characterized by adapting the fitness function to each problem stated, which makes it a very attractive one, thanks to the constant evolution and new demands that come from the radio optimization. In the developed tool, the aim is to conduct a study to find the best application method of the GA, in the problem in analysis. Hence, the methods used were:

- Selection Operator: Roulette Wheel, Tournament and Rank Selection.
- Crossover Operator: Single Point, Two Point, Uniform and Arithmetic Crossover.
- Mutation Operator: Neighbor and Uniform Mutation.

More information about this methods can be found on [14, 15].

The GA procedure is based on the analysis of a population of potential solutions. Each population is comprised by a set of individuals, each of those with a set of parameters named as genes. The algorithm is developed in continuous iterations. In each of those, the set of individuals is being changed according to rules that replicate the natural evolution. A population is represented by a matrix with the size $N_{pop} \times N$, where N_{pop} means the population size and N means the number of antennas being analyzed. Each individual is comprised by the tilt value codification (electrical tilt and combination of electrical tilt and mechanical tilt) of each station, which means it has a size of $1 \times N$. Each iteration of the algorithms aims to reproduce a generation of living organisms and each combination of tilt represents the individuals' genes.

The algorithm starts by analyzing N_{pop} individuals that belong to the population corresponding to the first generation. The individuals are randomly generated, according to the available variation of the tilt parameters adjustment. The proper exploration of the research environment and size of the population, as well as the definition of parameters with the probability of crossover, mutation and elitism are crucial to assure that an exhaustive analysis of all the possible solutions is conducted without an excessive increase of the simulation time.

All the individuals should be evaluated according to an adaptability function. This function is accountable to attribute a numerical value to each individual generated and, like this, it can evaluate the potential of each one to solve a specific problem. After the first evaluation, if there is any individual that satisfies the problem goals, thus, if this value is higher or equal to a specific threshold Th_{obj}, the individual is suggested as the solution to the genetic algorithm and the process ends. Otherwise, and if the iteration number has not reached a threshold Th_{it} (maximum number of iterations allowed), the algorithm keeps on with the probabilistic selection of individuals of the current generation (parents) that afterwards move to the crossover, mutation processes. In this way, a population of children is created that goes through a new evaluation process. This process repeats itself until the defined goal is achieved or until it is not possible to conduct more iterations. This process is illustrated in figure 3.

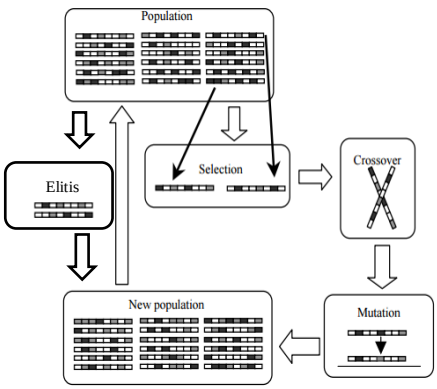

Fig. 3. A typical genetic process.

Fitness Function

The adaptation stage is conducted through the usage of a fitness function, $F\_obj(\theta, \varphi)$. In order for the GA to retrieve the best possible solution, the function implemented needs to be the one that best describes the problem. The evaluation function is responsible to give a fitness meaning to the numerical value achieved by each individual. The comparison of the individual fitness values consists of a survival and reproduction competition in a specific environment. The individuals with the best fitness values have a higher probability of being selected.

In this study, we adjust the parameter regarding the slope angle of a set of antennas installed in the urban area in the city of Lisbon, in order to achieve three goals:

- To minimize the number of samples with poor coverage or with coverage holes: geographical points in which the signal received is below a certain predefined limit;
- To reduce the intercells interference level;
- To reduce the pilot pollution that occurs, when in a specific area strong signal levels are identified, originated from more antennas than those that the Active Set comprises. A strong signal level is considered when the difference between the signal received by an antenna is lower than a certain margin (typically 5 dB) comparing to the best antenna.

For the development of the objective function, we need to take into account which are the available parameters and the metrics to consider. Some of the parameters defined are given by the Drive Test, some others assume typical values. Both of them are listed below:

- Parameters/stations inputs
  - Pt ($CPICH\ POWER$) of the N antennas;
  - Height of the N antennas;
  - Coordinates of the N antennas;
  - Electrical Tilt of the N antennas;
  - Mechanical Tilt of the N antennas;
  - Azimuth of the N antennas;
  - Adjacent cells list. This list was done manually, based on a visual criteria through the analysis of the network topologies, with the help from Google™ Earth;
  - Maximum Active Set allowed (AS_{max}), defined by the developer with the value of 3.
- Parameters/inputs of the samples retrieved from the Drive Test
  - $CPICH\ RSCP$ values in each j samples;
  - $CPICH\ \frac{Ec}{N0}$ values in each j samples;
  - Coordinates of the j samples.
- Metrics:
  - Number of j samples where $CPICH\ RSCP \leq Th_{rscp}$ in each N antenna;
  - Number of j samples where $CPICH\ \frac{Ec}{N0} \leq Th_{Ec/N0}$ in each N antenna;
  - Number of strong signals received by a specific terminal that are higher than those comprised in the Active Set (AS_{max},). It is defined as a strong signal that with a value of $CPICH\ RSCP \leq CPICH\ RSCP_{best} - 5dB$. That is, number of j samples where $(CPICH\ RSCP \leq CPICH\ RSCP_{best} - 5) \geq AS_{max}$;
  - Average $CPICH\ RSCP$ from all the samples in all the cells, in a specific percentage (%) of samples;
  - % of samples with a level below a value of $PICH\ RSCP$.

The goal of the latter two is to evaluate if there was a signal degradation between the first and the last moment.

In those cases when the function aims to solve more than one goal at the time, there are two possible approaches. The simplest approach consists on combining all the goals in just one function (by assigning weights). Another option is to find the set of optimal *Pareto* solutions. This means that it is not possible to keep on improving a goal's fitness without eroding the others. For example, let us imagine that the study scenario comprises 12 tri-sectored cells, which means 36 sectors, each one with a parameter that can assume 7 different values (for example, the electric downtilt can change between 0 and 6 degrees). In this way, the problem's domain would have $7^{36} = 2.6517E^{30}$ possible configurations to analyze. This is one of the reasons why the objective function should be defined following the first approach when we apply a GA to a mobile network, otherwise the simulation time would increase exponentially.

In order to achieve the goals that this work has established, a set of functions that served as parameters for the evaluated function, fitness, have been defined. Therefore, three intermediate functions $F1(\theta,\varphi)$, $F2(\theta,\varphi)$ and $F3(\theta,\varphi)$ have been formulated, each one related with the corresponding goal:

$$F1(\theta,\varphi) = \sum_{n=1}^{N}\left[\frac{\sum_{j=1}^{J} f1(CPICH\ RSCP_{j,n} - Th_{rscp})}{J}\right] \quad (4)$$

$$f1(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (5)$$

$$F2(\theta,\varphi) = \sum_{n=1}^{N}\left[\frac{\sum_{j=1}^{J} f2(CPICH\ Ec/N0_{j,n} - Th_{Ec/N0})}{J}\right] \quad (6)$$

$$f2(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (7)$$

$$F3(\theta,\varphi) = \frac{\sum_{j=1}^{J} f4\left[\sum_{n=1}^{N} f3(CPICH\ RSCP_{j,n} - (RSCP_{best} - 5))\right]}{J} \quad (8)$$

$$f3(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (9)$$

$$f4(x) = \begin{cases} 0, & x > AS_{max} \\ 1, & x \leq AS_{max} \end{cases} \quad (10)$$

$$F\_obj(\theta,\varphi) = p1 \times F1(\theta,\varphi) + p2 \times F2(\theta,\varphi) + p3 \times F3(\theta,\varphi) \quad (11)$$

Where, θ and φ relate to the electrical and mechanical tilt angle value, correspondingly. N related to the total number of antennas and J the total number of samples comprised in the coverage area of each cell. It was considered as coverage area of each antenna all the samples in which this it was best and also all the samples in which it provides only less 3 dB than its best. It is defined as best cell the antenna that provides the best signal to the mobile device in that geographical point. The symbols $p1, p2\ e\ p3$ represent the weights assigned to each goal and should be defined by the operator, according to the importance/priority of each goal defined.

Finally, the objective function still related with the last two metrics mentioned. These are priorities, which mean, either the solution follows the requirements or it receives a fitness value of zero. In this way, we avoid making choices that, even though they align with the previous goals, they erode the region coverage, when compared to the initial version. This criterion decreases the algorithm simulation time.

For this, we use the Cumulative Distribution Function (CDF), in which we evaluate:

- Signal level in the 60% of the total samples $RSCP(60\%)$. This value shows that 60% of the samples receive a signal level lower or equal than the one mentioned.
- Percentage level of the total samples in which signal level is lower or equal than -95 dBm: $\%(-95\ dBm)$

It is intended, with these two indicators, to admit that the algorithm accepts a solution that erode the average signal level but, according to some boundaries, in order to guarantee that the eroding level is not excessive. In this stage it is compared the initial configuration with the evaluated configuration. The algorithm accepts solutions that show a degradation of 3 dB when compared to the initial situation. As an example, if in an initial situation 60% of the samples have a coverage level below the -85 dBm, we accept values until -88 dBm. On the other hand, we validate which is the percentage of samples that receive signal levels below -95 dBm and, similar to the previous validation, we also only accept solutions in which the percentage number of samples with levels lower than -95 dBm is smaller than a maximum of 3% from the initial solution. In this way, two other functions are defined:

$$F4(x) = \begin{cases} 1, & RSCP_{final}(60\%) \geq RSCP_{inicial}(60\%) - 3dB \\ 0, & c.c \end{cases} \quad (12)$$

$$F5(x) = \begin{cases} 1, & \%_{final}(-95dBm) \geq \%_{inicial}(-95dBm) - 3\% \\ 0, & c.c \end{cases} \quad (13)$$

$$F_{obj(\theta,\varphi)} = \left(p1 \times F1(\theta,\varphi) + p2 \times F2(\theta,\varphi) + p3 \times F3(\theta,\varphi)\right) \times F4(x) \times F5(x)) \quad (14)$$

$$F\_obj(\theta,\varphi) = p1 \times F1(\theta,\varphi) + p2 \times F2(\theta,\varphi) + p3 \times F3(\theta,\varphi) \quad (15)$$

The GA aims to seek the value that maximizes the objective function. It is important to underline that in this study it is not supposed the adjustment of the parameters of CPICH Power neither the azimuth angle. It is intended to prove that only with the aid of RET and with small adjustments in the antenna's direction it is possible to increase strongly the network quality. Avoiding to spend resources in exhaustive network planning, time in adjustments in the propagation models used and material and operational costs in the stations inclusion/removal.

C. Optimization Tool

The MatLab® was the software elected to develop the tool used for coverage optimization and interference reduction for a given geographic area. Coverage optimization tests were performed in three different ways: coverage optimization by changing the electrical tilt in one or N stations and combining both electrical and mechanic tilt.

This tool offers the possibility to use the real terrain elevations, using Google Maps Elevation API for the given scenarios. To validate the RET as the only optimization parameter, simplify the monitoring process and to get better coverage results, were performed extensive tests of each type. It is possible to limit the performance tests for a single antenna in a specific area or simulate a real network. To get the real configurations and results, the simulation that runs the algorithm uses the Drive Tests supplied by Celfinet. The Drive Tests have collected the real measures along the driving path using a mobile terminal. These parameters are the inputs on the algorithms that are being used.

There are two different procedures in the optimization process, one for test 1 and the other for 2 and 3.

- Procedures for test 1:
  - Choose the antenna according to its SC;
  - Evaluating functions defined in the x section as $F1(\theta,\varphi)$, $F4(\theta,\varphi)$ e $F5(\theta,\varphi)$;
  - $F_{obj(\Psi)}$ function maximum.
- Procedures for 2 and 3 tests:
  - Range choice for mechanical and electrical tilt;
  - Run the genetic algorithm to get the maximum value of the objective function $F\_obj(\theta,\varphi)$.

For results demonstration, the tool returns the information about the comparative values between the initial and the final conditions function objective graphics along the iterations, cumulative distribution functions comparisons between initial and final conditions. In addition, a Google Earth interface and tests are shown with the initial vs final configuration parameters and simulation times.

IV. Results

The tool was developed to be used in two different project stages. On the planning phase, a correct network configuration is demanded, to avoid further expenses on changes or reconfigurations. The simulation time is not significant. On the other hand, on the optimizing phase, the response time is crucial to avoid network interruptions, consequent resource expenses and customer dissatisfaction.

For data analysis, it was defined that the selection between the various combinations of methods and parameters for the genetic algorithm, would be carried out according to the phases of its sequential execution. Thus, after the representational definition of each individual, the population size and the selection method is defined, then crossover operator and finally mutation.

A. Genetic Algorithm Parameters

From the performed analysis on the algorithm, the parameterization is defined on the following table 3. This table has the ideal parameters to be used on coverage optimization and interference reduction. It is important to note that these parameters were selected according to the test scenario in this paper, taking into account the recommended standard values. If the scenario is different a new validation should be performed.

TABLE 3
INITIAL PARAMETERS

Parameters	Value
Population Size	50 Individuals
Selection Operator	Tournament
Crossover Operator	Uniform
Crossover Probability	85%
Mutation Operator	Uniform
Mutation Probability	2%
Elitism Number	2 Units

The population size is chosen aiming the minimum simulation time and the adaptation of the algorithm, for the given characteristics. The problem complexity is proportional to the number of possible genes combinations that each individual can take [16]. If this number increases, the problem becomes more complex. Each gene represents a combination of both electrical and mechanical tilt, of each antenna.

According to the reference [17, 18], the optimum population size for less complex problem is from 20 to 30 individuals. However in this case, due to the high number of possible tilt combinations, a population of this size may lead to a premature solution. This way, a population of 50 individuals were selected because, according to the tests, a population with 100 individuals has the same performance but takes around 58.8% more time, table 4.

TABLE 4
OBJECTIVE FUNCTION (POPULATION SIZE)

Population Size	$F\_obj(\theta,\varphi)$	Simulation Time (500 iterations)
50 (Scenario 1)	0.931411	68 minutes
100 (Scenario 1)	0.936645	108 minutes
50 (Scenario 2)	0.959174	307 minutes
100 (Scenario 2)	0.964979	559 minutes

After the individual codification and population size is decided, there are three possible selections methods.

When the roulette method is applied, the simulation time is significantly higher than the tournament and rank methods. Also, the presented similarity between individuals in the objective function compromises the solution convergence. The selection methods by tournament or by rank have similar results, when compared with scenarios whose number of sectors is 12 (scenario 1). However, when compared with the 2nd or 3rd scenario, where the number of sectors and sampling is bigger, table 5, there is a big difference in the simulation time and necessary iterations to a solution convergence, comparing to the rank method. In this last method, all individuals must be classified and grouped before the selection process, which increments the simulation time. For these reasons the tournament method is selected. The characteristics of the first scenario are in the next section, while the ones of the 2nd and 3rd can be found in [14].

TABLE 5
OBJECTIVE FUNCTION (SELECTION METHOD)

Population Size	$F\_obj(\theta,\varphi)$	Simulation Time (Iterations until a convergence)
Tournament Selection (Scenario 2)	0.959174 (it=300)	184 minutes
Rank Selection (Scenario 2)	0.958242 (it=470)	282 minutes

The uniform crossover and mutation methods, are the most efficient in terms of diversity between individuals of the same population, with lower risk of converging to a local maximum. The simulation time of these algorithms are the same as the others crossover and mutation operator types.

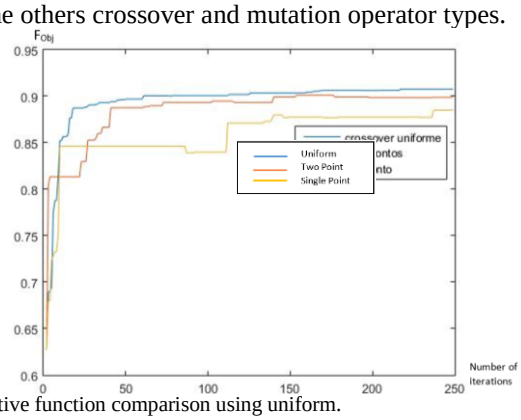

Fig.4. Objective function comparison using uniform.

As shown in the figure 4, the single point crossover (yellow line) is the method which has less variations on the objective function. This way, when the algorithm finds the optimum

local value, it has less capabilities of finding other problem domains, because the genetic exchange information is reduced.

In the other methods, it is possible to find more and better solutions during the iterative process. Between the uniform and two point crossover, the first achieves better results by promoting an exhaustive search between the all possible solutions, by selecting a random quantity of genes, contrarily to the two point crossover which does exchanges in sets of genes.

In the crossover method, is compared the crossover probability of 60% and 85%, as indicated on [17]. This values promote genetic diversity. As presented on the figure 5, the early convergence of the algorithm is promoted with 60%, because the fit individuals are selected with a bigger probability.

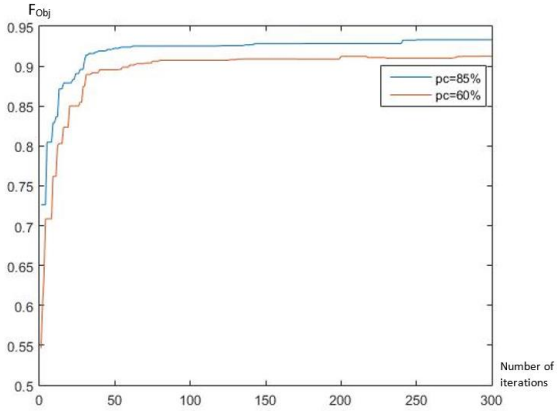

Fig. 5 – Objective function evolution using a crossover probability of 60% and 80%.

Between the two ways of applying this operator, the uniform mutation is elected, because the solution diversity and objective function variations are more significant when of the mutated gene value may change for any value within the available alphabet. This behavior can be observed by the difference of the objective function.

In the chosen method, a mutation probability of 0% to 10% [17], was validated. The random character of this solution becomes bigger with the increment of this probability. The mutation that exists between individuals allows to explore spaces in the problem domain.

The elitism consists on choosing automatically individuals with the best fitness function results for the next generation, without being submitted to the crossover and mutation operators. This method is the best for those situations where the objective value is not easily defined. It is applied an elitism of 4% in a population of 50 individuals, being advantageous to get the most optimized results.

B. Coverage and Interference Reduction Optimization

In this paper, a UMTS coverage optimization study is carried out, supported by extracted data from a real network in the Lisbon city. To test the algorithm, the electrical or the combination of both electrical and mechanical tilt is used as the optimization parameter, on the neighboring antennas.

In the test scenario, it is assumed that all antennas have the same parameterization, as present in the table 6. With this implementation it is intended to reduce the coverage holes, theoretically less than -120 dBm, and get a better signal in the already covered areas.

TABLE 6
ANTENNA CHARACTERISTIC

Characteristic	Value
Antenna Type	*Kathrein* 80010665
Frequency	2140 MHz
Antenna Gain	19.33 dBi
Polarization (º)	+45º
Downtilt range	[0º, 6]

The first test scenario (table 7) takes place between Bairro Alto, Baixa de Lisboa and Alfama, and has the following characteristics:

TABLE 7
NETWORK STATISTICS

Characteristic	Value
Number of Sites	12
Number of Sector (N)	26
Number of Samples (J)	2089
Area Size	$1500\,m \times 1500\,m$
Environment	Urban

Unique Sector

It is illustrated in the Figure 6 and 7 two examples of the optimization scenario for a single sector (test 1). On the first, there is a need to improve the coverage levels of the region near the antenna. After the algorithm execution there is a downtilt adjustment. Before the optimization, there is a mechanical tilt of 0º and electric downtilt of 4º. After the algorithm, the electric downtilt is 6º, increasing two negative values on the antenna's slope angle.

Fig. 6. Comparison between the initial and final RSCP level – (sector in red).

In the second scenario it is intended to increase the cell radius in order to intensify coverage at the cell boundaries. As a consequence the algorithm returns the uptilt adjustment indication to the initial value. Before the optimization, there is a mechanical tilt of 0º and electric downtilt of 4º. After applying the algorithm the electric downtilt is 1º, increasing three positive values on the antenna's slope angle. Both figures have a color schematic, representing the RSCP levels, obtained by the Drive Test measurements and estimated by the algorithm, respectively.

Fig. 7. Comparison between the initial and the final RSCP levels – (sector in green).

Multi Sector

In the figure 8 and 9 are present the results of the Drive Tests. In both figures the areas considered as critical are signed and numbered. The optimization process will focus on these zones.

Fig. 8. Initial power levels of the RSCP channel (Scenario 1).

In the figure 10 is presented in red the samples whose coverage level is below a certain limit value. Due to the technology, this value is theoretically -120 dBm, however the value of -95 dBm, that can be changed, was used for illustration.

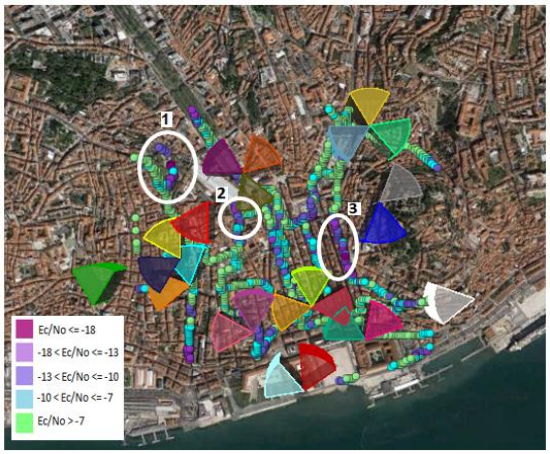

Fig. 9. Initial signal quality on the antennas (Scenario 1).

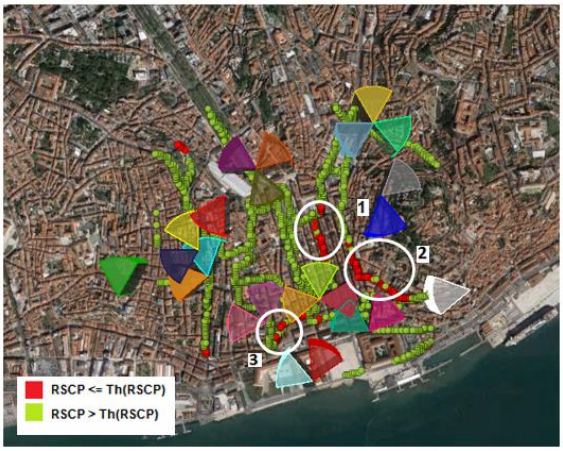

Fig. 10. Critical points before the optimization.

On the first approach, the RET is the only parameter to be changed. According to the results, the changes in the network configuration lead to a critical point reduction from 147 to 20 (Figure 11) and on an improvement in the curve of the CDF, which represents the percentage of samples on the coverage levels. The RSCP signal levels after optimization are in the Figure 12.

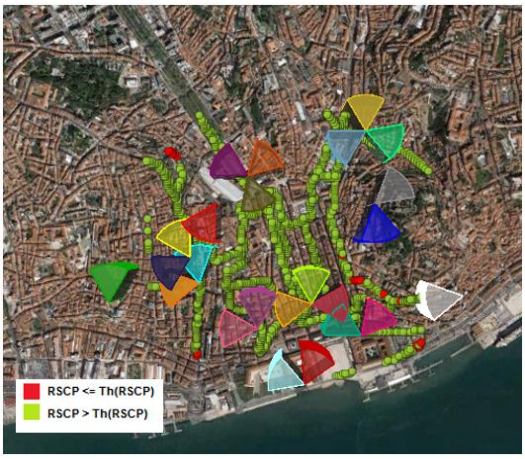

Fig. 11. Critical points after the optimization.

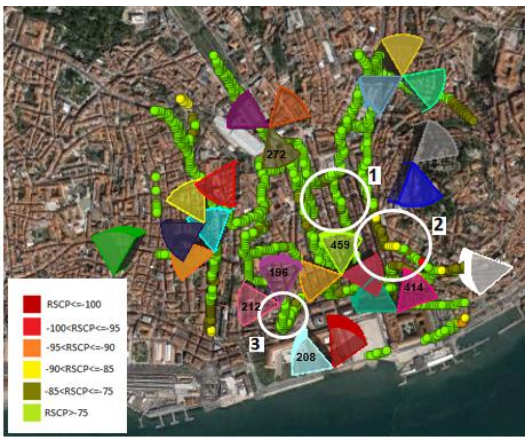

Fig. 12. RSCP signal levels after the optimization.

The white circles in the Figure 12, represents the critical areas which had the major improvements. The sectors responsible for this changes are present in the following table 8:

TABLE 8
TILT CONFIGURATIONS 1

SC	272	459	196	414	212	208
Initial Mechanical	2º UT	4º DT	0º	4º DT	2º UT	0º
Initial Electrical	4º DT	5º DT	4º DT	6ºDT	4º DT	4ºDT
Optimized Mechanical	2º UT	4º DT	0º	4º DT	2º UT	0º
Optimized Electrical	4º DT	1º DT	2º DT	0º	2 DT	5ºDT

DT stands for downtilt and UT for uptilt. After an analysis on the CDF of the figure 13, 30% of the number of samples have a coverage level below -71 dBm, 40% between -71 dBm to -60 dBm of RSCP and the last 30% above -60 dBm. Before the optimization, 30% had the RSCP bellow -78 dBm, 40% from -78 dBm to -63 dBm and the others 30% above -63 dBm.

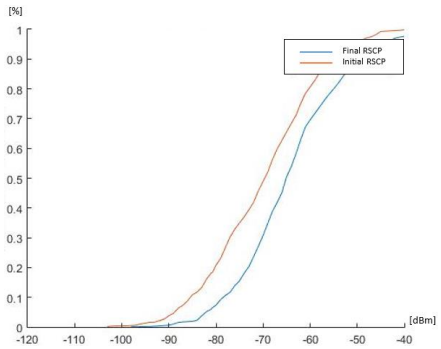

Fig. 13. CDF for RSCP values before and after the optimization for electrical tilt.

The signal improvements are visible on the figure 14 and 15. The sectors responsible for this changes are present in the following table 9:

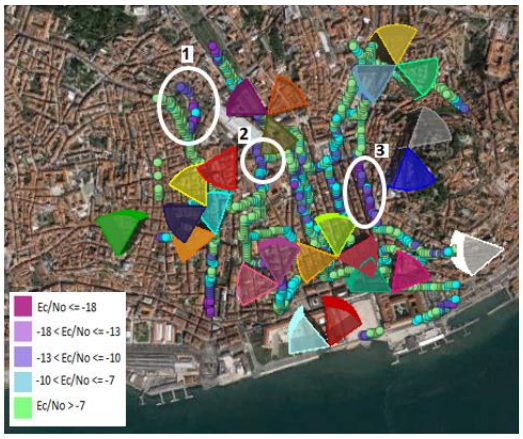

Fig. 14. RSCP signal levels after the optimization.

TABLE 9
TILT CONFIGURATIONS 2

SC	71	280	196	272	467	459
Initial Mechanical	0º	0º	0º	2º UT	2ºDT	4ºDT
Initial Electrical	0º	5ºDT	4ºDT	4ºDT	4ºDT	5ºDT
Optimized Mechanical	0º	0º	0º	2ºUT	2ºDT	4ºDT
Optimized Electrical	2ºDT	3ºDT	2ºDT	2ºDT	6ºDT	1ºDT

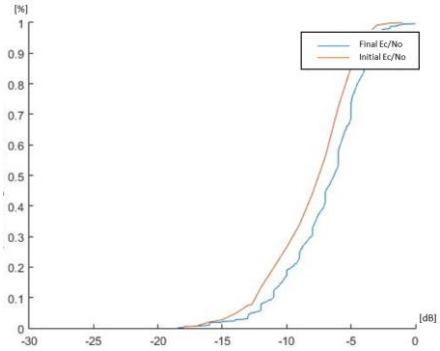

Fig. 15. CDF for signal quality levels before and after the optimization for electrical tilt.

This analysis indicates an improvement on the region's quality signal. The optimized CDF curve is 1dB to the right than in the beginning. However 1% of the samples have lower Ec/No levels than the worst case of the drive tests.

On the second approach, the electrical and mechanical tilts are changed for testing. The mechanical tilt requires a physical change in the site, making impossible to change this parameter automatically. However it allows a more precise adjustment. After an analysis on the CDF of the figure 16, 30% of the number of samples have a coverage level below -69.5 dBm, 40% between -69.5 dBm to -58 dBm of RSCP and the last 30% above -58 dBm.

After the optimization, with mechanical and electrical tilt, there is a critical point reduction from 147 to 16. As shown before, using only the electrical tilt a reduction to 20 critical points were obtained. As in the results with the electrical tilt simulation, the CDF curve (Figure 17) is 1dB to the right than in the beginning, but in this case, the lower Ec/No levels in 1% of the samples were avoided.

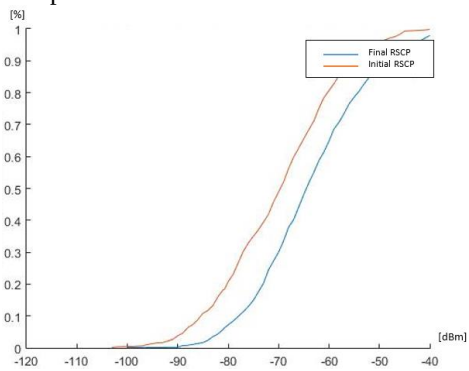

Fig. 16. CDF for RSCP values before and after the optimization for both tilts.

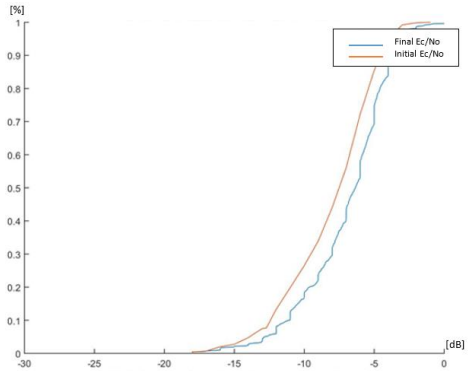

Fig. 17. CDF for signal quality levels before and after the optimization for both tilts.

Due to its remote possibilities and similar results in these optimizations, the RET was the chosen parameter to change.

V. Conclusion and Future Work

Along the current paper, a solution for coverage optimization and interference reduction in the 3G wireless access network have been achieved. For this, a genetic algorithm was chosen to find the best solution without involving a high computational cost, due to its metaheuristic characteristics. This study was supported by realistic network performance indicators.

A genetic algorithm was chosen due to its implementation simplicity and big adaptive capability to any given problem. It only needs a method to classify each possible solution, searching continuously in many regions on the search space, evaluating a group of solutions. This way, a big quantity of network parameters can be optimized simultaneously.

In this work, an analysis about the convergence and computational complexity for the present algorithm was present. The best results were achieved with a population of 50 individuals, tournament selection, uniform crossover of 85% and uniform mutation with 2% of occurrence, in a simulation time between 1 to 5 hours, depending on the given scenario. In the case of a different scenario or more parameters added, a new analysis has to be done.

It was proposed an algorithm that has the goal to decrease the coverage whole or weak coverage, avoid cell overlap and consequent interference zones and reduce the pilot pollution. For this, key performance indicators (KPIs) were used to define de validation metrics. This optimization process was developed over a study carried in different zones of Lisbon, Portugal.

The tilt was the selected parameter for the optimization process, driven by the ease of remote electrical tilt (RET). The RET is seen as one of the main tools for system optimizations, because can be handled remotely by the mobile operators. Changing it, the coverage area can be adjusted modifying the antenna radiation diagram, without compromising the Ec/No. According to this study, if the electrical and mechanical tilt are changed together, the results are slightly better than when optimized only by the electric tilt.

However, having these small differences, the RET is chosen by the operators to optimize their networks, ensuring a good coverage management, with the required quality levels, lower response/planning time and smaller operation costs.

With the proposed methodology, some improvements were taken for automatic optimizing tools and SON technics implementation.

For future developments, it is expected to implement these algorithms on capacity optimizations and adapt them for multi-technological coexistence between 2G, 3G and 4G.

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