# USE OF GENETIC ALGORITHM IN THE OPTIMISATION OF THE LTE DEPLOYMENT

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***ABSTRACT***

*The purpose of this paper is to evaluate LTE deployment and to optimize RF parameters that include sub-channel power, antenna down tilt, azimuth and beam-width. An integer optimizing based on genetic programming is developed by evaluating the signal-to-interference plus noise ratio. The simulation uses a static model based on an OFDMA module designed for a Long Term Evolution (LTE) network from 3GPP [TR36.942]. The site location and initial antenna parameters are taken from real GSM network already optimized for coverage. Our analysis shows that the LTE network performance could be increased by more than 45% by adjusting both cells power and antenna parameters.*

***KEYWORDS***

*LTE, RF Optimization, Antenna, Genetic algorithm, Wireless*

## 1. INTRODUCTION

The deployment of LTE networks represents a huge investment for operators, linked both to the cost of infrastructure and to the entry fees, paid in the form of licenses. The establishment of an access network represents about 80% of total investment in infrastructure. In this context, optimizing access network is a fundamental issue for an operator to save investments; reduce the number of sites to deploy, and to ensure good quality service to users.

Most telecom operators use manual radio optimization, based on empirical methods that are not systematic. We tried to automate this optimization in order to test a range of wider settings than the range allowed by manual optimization, and improving performance of existing networks already optimized manually for GSM network. Because of the large number of parameters to optimize and the complexity of the evaluation criteria, the choice of the combinatorial optimization approach was an imperative approach and the genetic algorithm is considered effective and efficient for this kind of problem.

In the literature, much work has been carried out in terms of optimization of cellular air interfaces. None of these reports relate on the optimization of LTE air interface. A method of planning an OFDM broadcast system is presented in [3] although this does not cover the implications of cellular operation. [4] and [5] show a method for optimizing coverage and handover in wide-band code division multiple access (WCDMA) via adjustment and minimization of pilot powers. In [6] a simple greedy algorithm is used to optimize RF Parameters in IEEE 802.16e, but this approach is simplified by using and optimizing only a hotspot BS selected each time by the optimizer. This approach may cause degradation in the other spots of the system. In our approach, we try to optimize the whole area by using a genetic algorithm. The processing time it takes for the simulator is about 2 days to simulate all the parameters.

This paper will be organized as follows: The first part describes the LTE profile used in our simulation. The second section describes the simulation methodology followed in our work. The third part presents a comparison of two meta-heuristics that lead to the choice of genetic optimization. In the fourth part, we draw the experimental results. Conclusions are presented in section 5.

## 2. LTE PROFILE

Long Term Evolution is a new technology in which radio interface is designed based on OFDMA in the downlink (DL) and Single Carrier – Frequency Division Multiple Access (SC-FDMA) in the uplink (UL). The work of 3GPP on the evolution of the 3G mobile system is aimed at achieving additional substantial leaps in terms of service provisioning and cost reduction. 3GPP has concluded a set of targets and requirements for Long Term Evolution in Release 8, on the basis of the LTE feasibility study [7], and the LTE requirements document [8].

To evaluate LTE deployment, the methodology agreed within LTE Ran4 [1] has been adopted. It is based on static Monte-Carlo simulation, and this is justified by the fact that during our genetic optimization many RF parameters must be evaluated. Moreover, dynamic evaluation is time consuming and will lead to several scenarios variations [2].
Furthermore, it is agreed to use Round Robin scheduler, full buffer traffic model and frequency reuse of 1/1.

The system used is depicted in **Error! Reference source not found.** and was created from real deployed GSM system that includes 99 cells; the UEs (denoted by red stars) are deployed randomly in the whole network region.

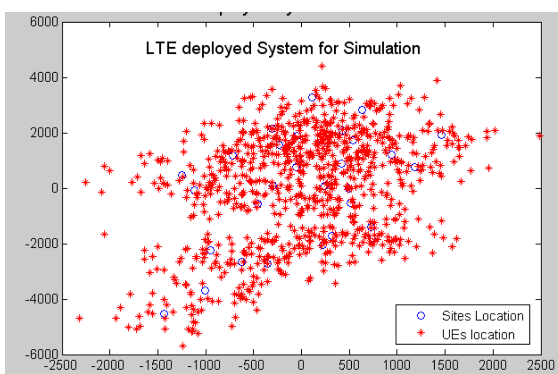


Figure 1: LTE deployed System for Simulation

The initial setting of the antenna used in our simulation is based on the real deployed GSM network and it includes the antenna high, the down Tilt and the azimuth of each cell and the antenna gain corresponding to a typical remote control antenna.

Our model assumes the following characteristics for LTE:
1) - LTE is implemented on 900 MHz and 10 MHz bandwidth is used.

2) - Base stations are transmitting at full power.
3) - Assumption: identical BS-MSS channel conditions for all sub-carriers, ignoring Rayleigh fading effects, and constant propagation loss.

## 3. SIMULATION METHODOLOGY

The simulation flow is developed from 3GPP standard simulation [1] as follows:

For i=1:# of snapshots

1. Distribute sufficiently many UEs randomly throughout the system area such that: to each cell within the HO margin of 3dB, the same number, ***K***, of users is allocated as active UEs.

   - Calculate the path loss from each UE to all cells and find the smallest path loss
   - Link the UE randomly to a cell to which the path loss is within the smallest path loss plus the HO margin of 3dB
   - Select $K$ UEs randomly from all the UEs linked to one cell as active UEs. These $K$ active UEs will be scheduled during this snapshot.
   - Note: a full load system is assumed, namely, all available resource blocks (RBs) will be allocated to active UEs. And each UE is scheduled with the same number $N$ of RBs. Thus, the BS transmit power per UE is fixed.

     Let $P_{BS}^{Max}$ denotes the maximum transmit power of BS

     $M = N \times K$ is the number of all available RBs in each cell

     $P_{BS}^{UE}$ is the transmit power from BS to the active UE, and

     $$P_{BS}^{UE} = P_{BS}^{Max} \frac{N}{M}.$$

2. Calculate DL C/I for all active UEs in all cells.

   Loop over all cells from $j=1$ to $N_{cell}$ . Loop over all active UEs from $k=1$ to $K$

   For the $k$ -th active UE in the $j$ -th cell (i.e. $UE_{j,k}$ ) its C/I is denoted by $\frac{C(j,k)}{I(j,k)}$,

   - $C(j,k)$ is the received power from the serving BS, i.e., the $j$ -th BS (here BS and cell are interchangeable)
   - $C(j,k) = P_{BS}^{UE} \times pathloss(UE_{j,k}, BS_j)$
   - $I(j,k)$ is the interference power which consists of other cell interference $I_{other}(j,k)$ and the thermal noise $N_t$ (In our simulation intersystem interference is ignored):

   $$I(j,k) = I_{other}(j,k) + N_t$$

   $$I_{other}(j,k) = \sum_{l=1, l \neq j}^{N_{cell}} P_{BS}^{UE} \times pathloss(UE_{j,k}, BS_l)$$

   $$N_t = 10 \wedge ((-174 + 10 \log 10 (bandwith\ of\ N\ RBs) + NoiseFigure_{BS}) / 10)$$

4. Determine the throughput for each UE with its C/I according to the link-to-system level mapping given in [1].

5. Collect statistics.

## 4. META-HEURISTIC ALGORITHM CHOICE

To select which algorithm will be used during our network optimization, two Meta-heuristic algorithms have been tested and evaluated: Genetic Algorithm and Simulated Annealing.
For our comparison, we have considered an omni-directional cell with 10 users, and we tried to optimize first one single parameter which is the sub-channel power. The test is repeated 33 times and the optimization is used by using the genetic algorithm and the simulated annealing.

The result shows that the two algorithms give almost the same range of results, as shown in the figure 2; however, the genetic algorithm increases rapidly the fitness function SINR 5 times better than the simulated annealing.

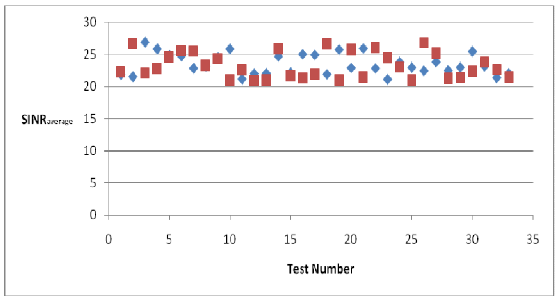


Figure2: Genetic and Simulated annealing Algorithms comparison

The genetic algorithm has been chosen as the main optimizer for our RF parameters and to perform integer programming using the GA function, a custom mutation function has been create that generates only integer outputs from the set of RF parameters listed in the table below:

| Parameter | Constraint |
|---|---|
| Antenna down-tilt | 0 to 8, every 2 degrees |
| Antenna azimuth | ± 30 degrees, every 15 degrees |
| Horizontal beam-width | 35, 65, 90, 120 degrees |
| Sub-Channel Power | 20 to 25 watt, every 1 degree |

Table 1: Adjustable Parameters for Simulation Scenarios

The evaluation function is the SINR average for all the mobiles connected to our system. The optimizer seeks to increase the SINR via the control of the antenna down tilt, orientation, the Horizontal beam-width and by changing the sub-channel Power.

## 5. EXPERIMENT RESULTS

The system comprises 99 cells and 9900 UEs deployed randomly in the area during each snapshot. In addition, the lognormal fading map is changing with a standard deviation of six.

We completed many test scenarios, where different subsets of adjustable parameters to be modified are defined, as described in Table I. This approach provides an initial assessment of the trade-off between economic cost and performance benefit for various models of remote control antenna with increasing flexibilities.

The time of simulation took between 5 to 10 minutes to optimize on standard PC depending on the number of the parameters to evaluate.

### 5.1. Scenario 1: Power optimization

In this experiment, we tried to optimize only the sub channel power by using the integer genetic algorithm. The powers will be adjusted from 20 to 25 watt every 1 degree indexed from 0 to 5 as shown in the figure 3 in which the average SINR has been improved from 8.6 dB to 9.8dB, the figure shows also the best sub-channel power for each cell.

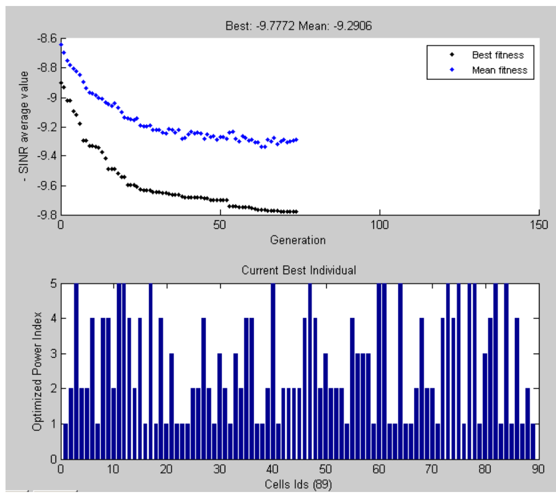


Figure 3: Power Optimization by integer Genetic programming.

This test has been repeated 300 times. Figure 4 below shows the CDF of the SINR before and after optimization; we can observe an improvement of 2% of the SINR.

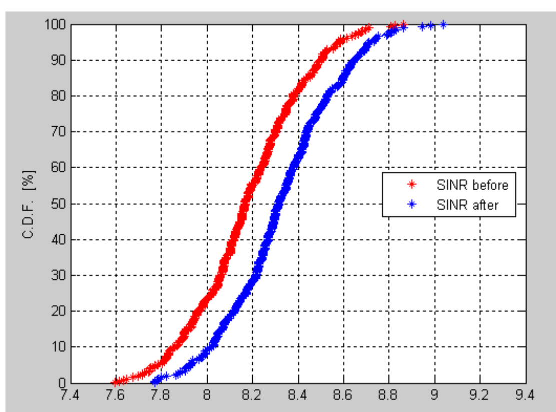


Figure 4: SINR CDF before and after optimization for Power optimization.

### 5.2. Scenario 2: Antenna parameters optimization

In this scenario, different antenna parameters are optimized using the genetic algorithm. Figure 5 shows the CDFs of the SINR in case of optimizing antenna tilt, antenna azimuth and antenna horizontal beam-width. We can notice that optimizing the antenna horizontal beam-width gives the maximum improvement of the SINR.

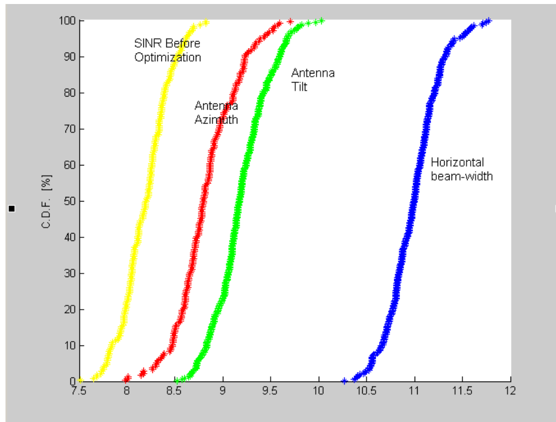


Figure 5: SINR CDF before and after optimization in case of antenna parameters optimization.

## 5.3 Scenario 3: **Power and Antenna parameters optimization.**

In scenario 3, two experiments have been carried out; the first is to optimize all the antenna parameters shown in table 1, and the second experiment is to evaluate all the parameters included in the table which include the antenna parameters and the sub-channel power. Figure 6 shows the CDFs of the SINR of the two experiments. We can note that the two scenarios give almost the same range of results.

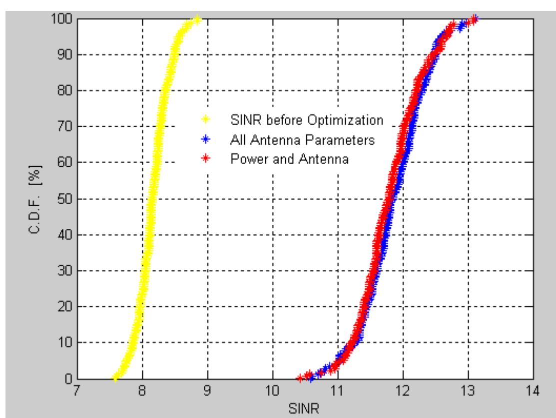


Figure 6: SINR CDF before and after optimization in case of adjusting all antenna parameters.

Table 2 shows, in average, the percentage improvement of SINR for different scenarios.

| Degree of Optimization | Mean (SINR) (dB) Before | Mean (SINR) (dB) After | Percentage Improvement |
|---|---|---|---|
| Subchannel Power | 8.18 | 8.32 | 2% |
| Antenna Horizontal beam-width | 8.19 | 11.01 | 34% |
| Antenna Tilt | 8.18 | 9.20 | 13% |
| Antenna Azimuth | 8.19 | 8.83 | 8% |
| All Antenna Paramters | 8.17 | 11.86 | 45% |
| Power and All Antenna Parameters | 8.16 | 11.91 | 45% |

Table 2: Percentage improvement on SINR for each scenario

## 3. CONCLUSIONS

In this paper, we have considered the problem of optimizing BS parameters of an LTE multi-cell system in order to improve the RF performance, particularly the SINR that leads to good coverage and high throughput of the system. Our optimizer is based on a genetic algorithm that allows adjusting many parameters to increase the SINR, based on model predictions. The optimizer was able to improve the system performance by more than 45%. It has been observed that the antenna parameter is likely to have the most significant impact on the improvement, particularly the antenna horizontal beam-width and the antenna Tilt, where Sub-channel power are likely to be the less effective.

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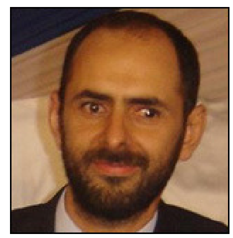

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