5G-Optimizing Network Coverage in Radio Self Organizing Networks by M/L Based Beam Tilt Algorithm

Premkumar Karthikeyan, Nagabushanam Hari Kumar(✉), and Srinivasan Aishwarya

Ericsson Research India, Tamarai Tech Park, Guindy, Chennai, India
p.karthikeyan@ericcson.com, n.hari.kumar@ericsson.com, aishwaryasrini94@gmail.com

Abstract. This paper proposes a novel machine learning based antenna beam tilt algorithm for minimizing the overall Poor Signal Strength (PSS) regions / dead zones in the network area considered. Our objective is to provide network intelligence and automation of the optimization of the configurable parameter, azimuth angle of the antenna, to adapt to varying channel conditions and rebalance the entire network so as to provide an optimized level of service to the users. The proposed scheme involves developing a simulation scenario for the existing network and employing machine learning to study the behavior of the network by taking large number of combinations of azimuth angles and corresponding measure of PSS area. Regression analysis and stochastic gradient descent are used to obtain the relationship and the optimized angles for which the PSS area is minimum. Our simulation results demonstrate the reduction in overall PSS area compared to state of art approaches.

Keywords: eNodeB · Azimuth angle · SINR (Signal to Interference Noise Ratio) · Long Term Evolution · Self Optimizing Network · CQI (Channel Quality Indicator)

1 Introduction

With a rapid growth of cellular radio networks and soaring number of mobile users all over the world, there is an increasing demand for enhanced user experience in terms of good coverage and cell capacity. Initial deployment of a radio network includes RF planning. RF Planning is the process of assigning frequencies, transmitter locations and parameters of a wireless communication system to provide sufficient coverage and capacity for the services required. Automatic planning tools are employed to perform detailed predictions of number of sites and site locations, antenna directions and downtilts, neighbor cell lists for each site, mobility parameters for each site, frequency plan and detailed coverage predictions (SINR, CQI and user location). The characteristics of the selected antenna, the terrain, the land use and land clutter surrounding each site, which provide a better estimate of the coverage of the sites are also taken into account in RF planning. Thus, the initially established network is optimum. In due course of time, absorption loss arising due to edifices, interference from the neighboring

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eNodeBs and other environmental changes cause signal deterioration in certain regions where the Signal to Interference and Noise Ratio (SINR) drops below the desired value. Apart from these reasons, sudden eNodeB failures may also lead to the formation of such regions and the users are affected. Hence, continuous optimization of the network to accommodate the changes in the environment or additional service requirements (e.g. additional coverage or capacity) is inevitable. This process includes collection of measurement data on a regular basis. The data is then used to optimize the parameters (e.g. antenna orientation, downtilt, frequency plan) of existing sites.

1.1 Objective

Present day solutions to reduce dead zone includes installing femtocells, reflectors, manually tilting the antenna etc. Our ultimate goal is to eliminate the manual operational tasks involved in reducing the dead zone, through an automated mechanism called self-optimizing network. Our aim is to provide the maximum possible network coverage to the users in a location considered, irrespective of the environmental and climatic conditions prevailing in that region and thereby increase the number of users and profit for the network operator. The scope of this paper lies in the Self-Optimizing capabilities of the Long Term Evolution, which has been standardized in the 3GPP Release 8 and Release 9.

2 Long Term Evolution – Introduction

LTE stands for Long Term Evolution and it was started as a project in 2004 by telecommunication body known as the Third Generation Partnership Project (3GPP). The main goal of LTE is to provide a high data rate, low latency and packet optimized radio access technology supporting flexible bandwidth deployments. Its network architecture has been designed with the goal to support packet-switched traffic with seamless mobility and great quality of service. LTE is the successor of UMTS and CDMA 2000. It supports flexible carrier bandwidths, from 1.4 MHz to 20 MHz as well as both FDD and TDD.

3 Self Organizing Networks – Introduction

A self-organizing Network is an automation technology designed to make the planning, configuration, management, optimization and healing of mobile radio access networks simpler and faster. SON has been codified within 3GPP Release 8 and subsequent specifications in a series of standards including 36.902. The first technology making use of SON features is the Long Term Evolution. In a typical situation, when the network elements begin to underperform, operators need to manually track down the root cause and develop optimization solutions. With smart SON, operators can sit back and see the network manage itself. SON makes use of the real time radio resource information to provide the required solutions. It makes effective, impactful adjustments to a wide variety of configurable parameters such as antenna tilts, antenna power outputs etc. Based on the functionality of the SON algorithms used, it can be classified into three types – self configuration functions, self optimization functions, self healing functions.

3.1 Self Optimization Functions

Every base station contains hundreds of configuration parameters that control various aspects of the cell site. Each of these can be altered to change network behavior, based on observations of both the base station and measurements at the mobile station or handset. Functions of self-optimization are included in 3GPP Release 9. It includes optimization of coverage, capacity, handover and interference. The algorithm devised falls in this category of SON solutions. It involves optimization of coverage by adjusting the tilt of the antenna. In other words, the azimuth angles of all the eNodeB antenna radiation patterns are adjusted to achieve minimum dead zone region in a network considered (Fig. 1).

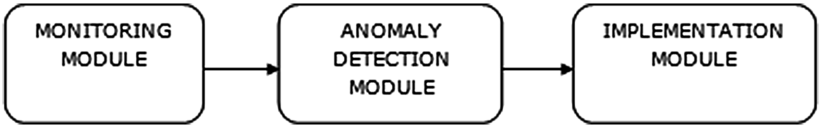


Fig. 1. Self Optimizing Network block diagram

The above diagram illustrates the major modules involved in a self-optimizing network.

- **Monitoring Module:** This module maintains a record of the total number of UEs in its particular cell site, number of neighboring eNodeBs, channel conditions, current location of all UEs, signal strength experienced by each UE in terms of SINR or CQI and other necessary network parameters. This information is constantly sent as feedback to the eNodeBs by the UEs. This data set is the input for the algorithm.
- **Anomaly Detection Module:** As the name implies, this module keeps track of the previous module's record and reports to the administrator if there are any deviations in the network performance parameter values. i.e. if the network performance is poor. In the case considered, this module acts whenever the SINR or CQI value at any particular location in the network approaches a threshold value set by the network administrator.
- **Implementation Module:** Following the data analysis step, optimization algorithm and corrections will be triggered automatically to make decisions on how to operate the system according to user's needs. The implementation module executes the algorithm to optimize the network. It basically involves the creation of virtual simulation scenario for the deviated network using the Vienna LTE Simulator as carried out in the project. The antenna azimuth angle is chosen as the parameter of

configuration for the project. This module uses machine learning principles to obtain the azimuth angles for which the network is optimized i.e. the dead zone region is minimized. In other words, the horizontal tilt of the main lobe is adjusted to cover up the dead zone.

4 Azimuth Angle of Antenna

Azimuth angle is defined as the horizontal angle measured clockwise from the north base line. It is measured in degrees (Fig. 2).

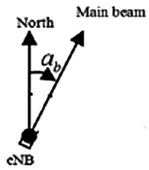


Fig. 2. Azimuth Angle

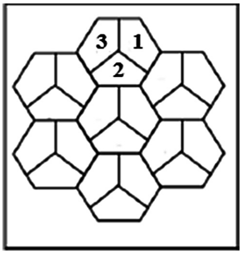


Fig. 3. Network Scenario

Figure 3 shows a simple 7 cell network with hexagonal cells containing 3 sectors with an azimuth span of 120° each. The following table shows sector number and corresponding azimuth angle span (Table 1).

Table 1. Azimuth Angle Span

Sector	Azimuth Angle Span
1	0–120
2	121–240
3	241–360

5 Machine Learning

Machine Learning explores the construction and study of algorithms that can learn from data. Supervised machine learning has been adopted. The existing network is studied by means of setting various azimuth angles to all the base station antennas and the corresponding dead zone measure is obtained. Ultimately, a table of nearly 1800 entries for various combinations of azimuth angles with the dead zone measure is drawn.

5.1 Multi Polynomial Regression

Regression analysis is a statistical process for estimating the relationship among variables. With respect to this paper, there are 21 independent variables which are the azimuth angles and one dependent variable which is the dead zone measure. The data fetched in the previous process is fed as input to the regression algorithm. The output of the algorithm is a polynomial equation that shows the relationship between the independent variables and the dependent variable.

$$y = a1 * x1 + a2 * x2 + a3 * x3 + \ldots\ldots\ldots\ldots\ldots\ldots + a21 * x21 \tag{1}$$

where “y” is the dead zone measure, “a1 to a21” are constants and “x1 to x21” are azimuth angle variables.

5.2 Stochastic Gradient Descent

Gradient descent is a first-order optimization algorithm. To find a local minimum of a function using gradient descent, one takes steps proportional to the negative of the gradient (or of the approximate gradient) of the function at the current point and the iteration proceeds until local minimum is reached. The algorithm is illustrated in the following steps.

- The objective function obtained from regression is given as input to the stochastic gradient descent algorithm.
- Choose an initial vector of parameters “x” (x1 to x21) and learning rate “alpha”.

  - ```
    for i=1,2,3….n
      for r=1,2,3…..21
       g=gradient(x,r);
       xnew = x – alpha*g;
       x=xnew;
      end
    end
    ```

  where “i” denotes number of iterations
    ```

"r" denotes the subscript of x, for example if r = 2, it denotes the variable x2
"alpha" is the learning rate and its value is 0.05
"g" is the partial first order differentiation of the function with respect to (x, r)

Thus, the output of this algorithm is shown in the figure below.

6 Simulation and Results

The LTE cellular radio network scenario and the algorithm have been coded and simulated using MATLAB 2012a. The following sections describe the steps involved in the algorithm.

6.1 Creation of Virtual Simulation Scenario for Existing Network

The first step involved in this process is to simulate the real time existing network in Matlab. The frequency in which the system is operating is 2 GHz and the system bandwidth is 5 MHz. Totally 7 eNodeBs are established in a region of 1200sqm. The map resolution is 5 pixels per meter and so there are 241*241 = 58081 pixels in the color map. The minimum coupling loss for macro cell urban area is set as 70 dB. The pathloss model used in this simulation scenario for a carrier frequency of 2 GHz is given by the following formula.

$$\mathrm{L} = 128.1 + 37.6\log_{10}(\mathrm{R}) \tag{2}$$

where L is the pathloss and R is the eNodeB-UE separation in Km. The eNodeB transmit power is 43 dBm/20 W as given in [1]. The UE receiver noise figure is 9 dB as mentioned in Table 12.2 of [1]. Thus, the initial network setup is simulated with the above mentioned parameters and the resultant figures are shown (Figs. 4 and 5).

Figure 6 shows the plot of SINR values at various distances from the eNodeBs. With respect to this paper, the regions where power level is below −98 dBm (blue region in the heat map) are considered as dead zones.

6.2 Multi-polynomial Regression Output

The output of multi polynomial regression is given as follows

$$\begin{aligned} \mathrm{y} = {} & 34.622 * \mathrm{x21} - 11.401 * \mathrm{x20} + 0.133 * \mathrm{x20} * \mathrm{x21}\ldots\ldots + 0.1585 * \mathrm{x20}^2 \\ & + 0.0352 * \mathrm{x21}^2 \end{aligned} \tag{3}$$

where "y" is the dead zone measure and "x1 to x21" are the azimuth angles.

The following figure shows the correctness of the equation obtained by regression analysis (Figs. 7 and 8).

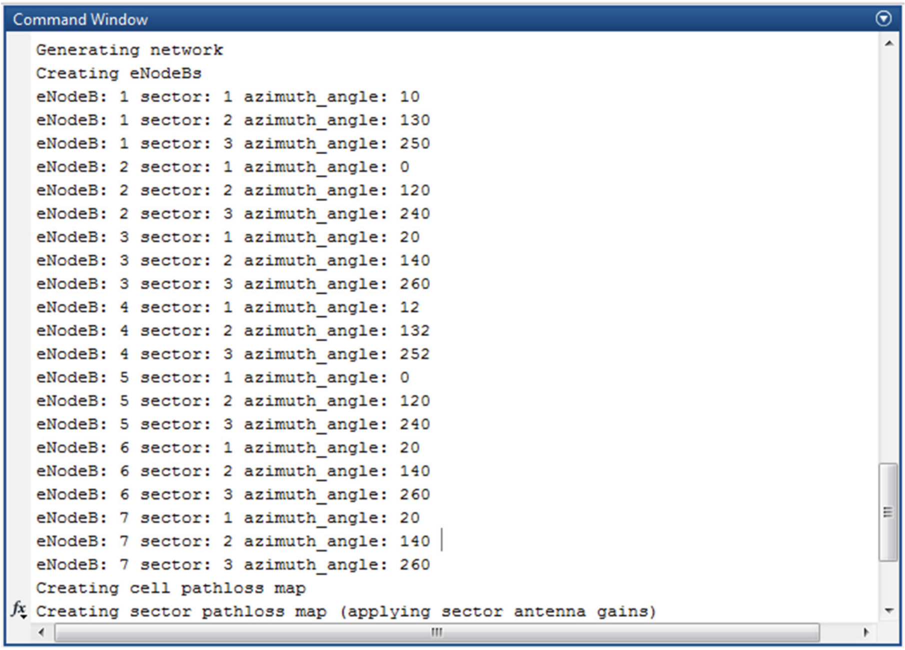


Fig. 4. Azimuth Angles of antennas in existing network

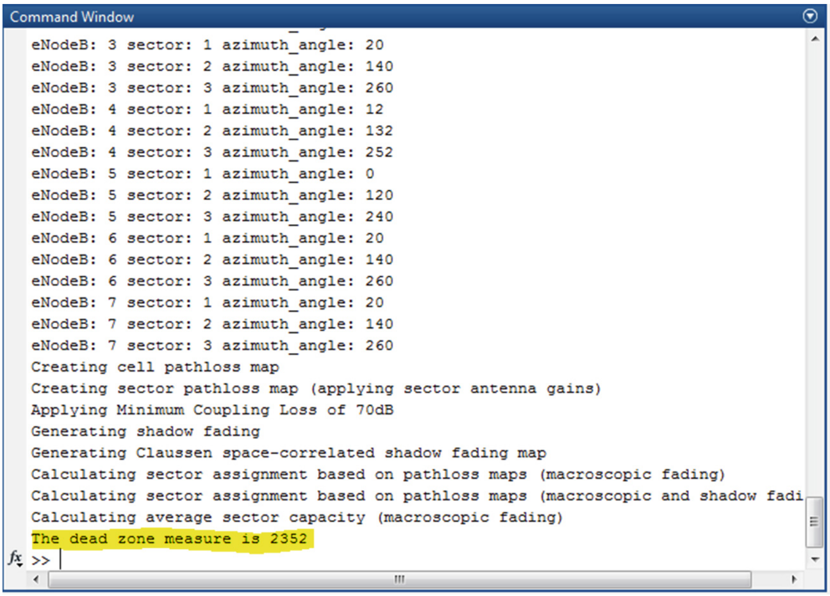


Fig. 5. Dead Zone measure in the existing network

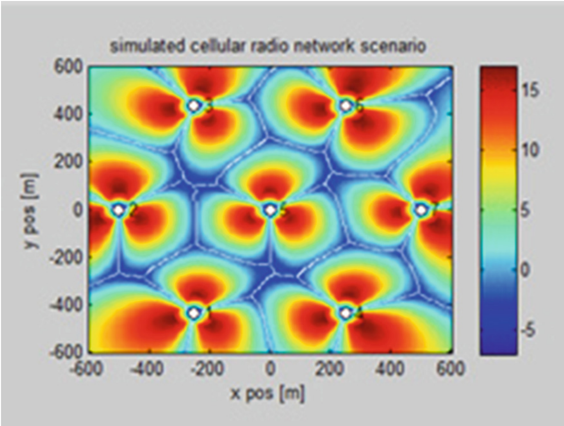


Fig. 6. Color map of the existing network (Color figure online)

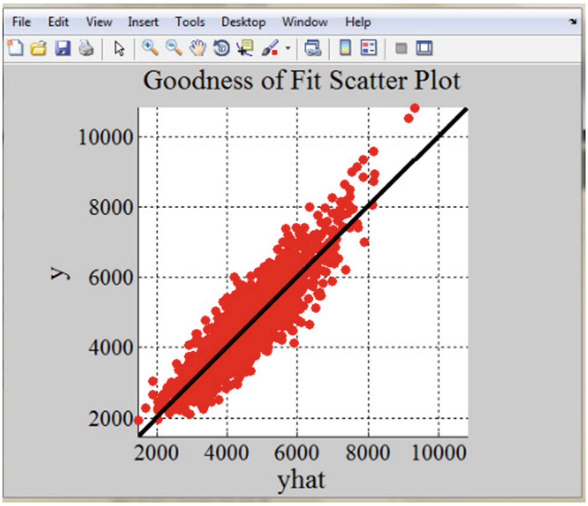
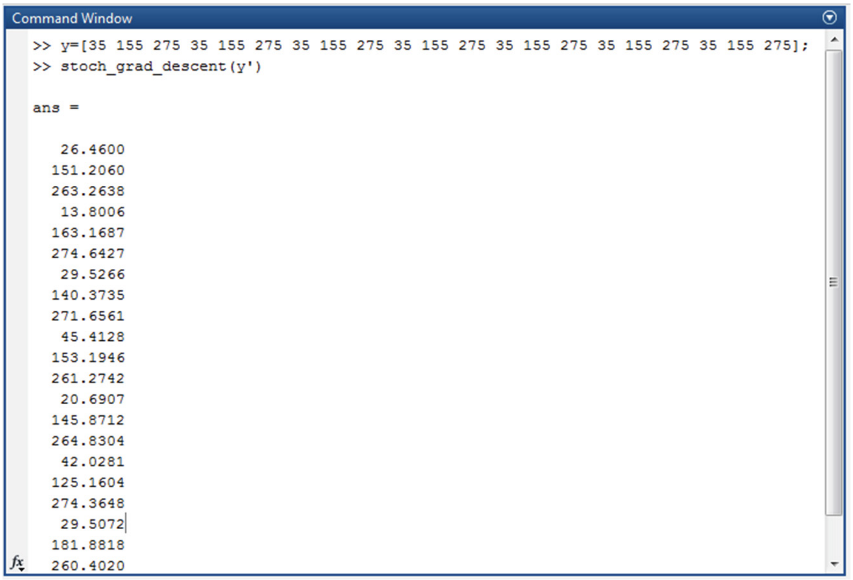


Fig. 7. Goodness of fit

6.3 Stochastic Gradient Descent Output

The angles obtained from the above step are fed into the eNodeBs and the resulting network is shown as simulation results below (Figs. 9 and 10).

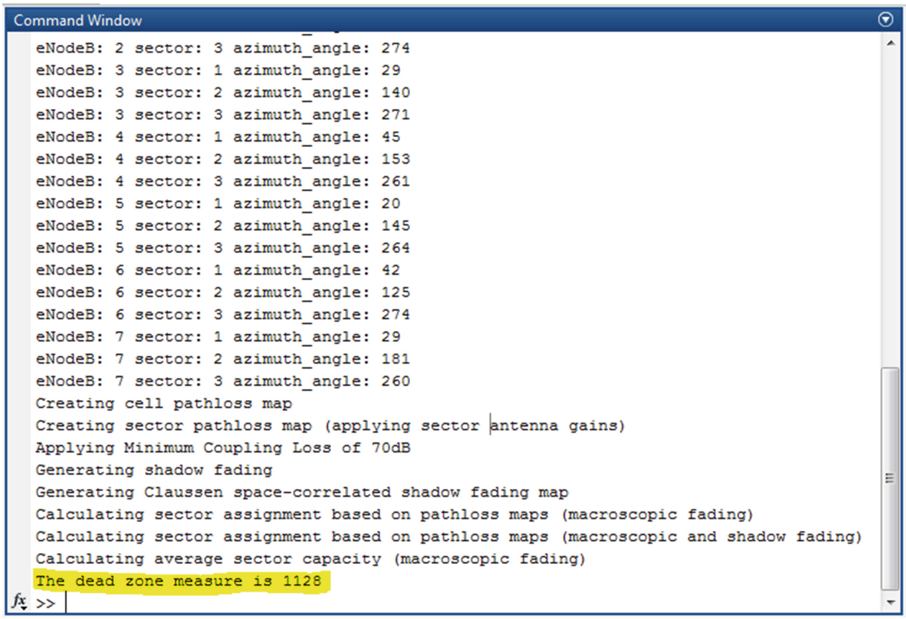


```
Command Window
>> y=[35 155 275 35 155 275 35 155 275 35 155 275 35 155 275 35 155 275 35 155 275];
>> stoch_grad_descent(y')

ans =

   26.4600
  151.2060
  263.2638
   13.8006
  163.1687
  274.6427
   29.5266
  140.3735
  271.6561
   45.4128
  153.1946
  261.2742
   20.6907
  145.8712
  264.8304
   42.0281
  125.1604
  274.3648
   29.5072
  181.8818
  260.4020
```

Fig. 8. Output azimuth angles



```
Command Window
eNodeB: 2 sector: 3 azimuth_angle: 274
eNodeB: 3 sector: 1 azimuth_angle: 29
eNodeB: 3 sector: 2 azimuth_angle: 140
eNodeB: 3 sector: 3 azimuth_angle: 271
eNodeB: 4 sector: 1 azimuth_angle: 45
eNodeB: 4 sector: 2 azimuth_angle: 153
eNodeB: 4 sector: 3 azimuth_angle: 261
eNodeB: 5 sector: 1 azimuth_angle: 20
eNodeB: 5 sector: 2 azimuth_angle: 145
eNodeB: 5 sector: 3 azimuth_angle: 264
eNodeB: 6 sector: 1 azimuth_angle: 42
eNodeB: 6 sector: 2 azimuth_angle: 125
eNodeB: 6 sector: 3 azimuth_angle: 274
eNodeB: 7 sector: 1 azimuth_angle: 29
eNodeB: 7 sector: 2 azimuth_angle: 181
eNodeB: 7 sector: 3 azimuth_angle: 260
Creating cell pathloss map
Creating sector pathloss map (applying sector antenna gains)
Applying Minimum Coupling Loss of 70dB
Generating shadow fading
Generating Claussen space-correlated shadow fading map
Calculating sector assignment based on pathloss maps (macroscopic fading)
Calculating sector assignment based on pathloss maps (macroscopic and shadow fading)
Calculating average sector capacity (macroscopic fading)
The dead zone measure is 1128
>>
```

Fig. 9. Dead zone measure of the optimized network

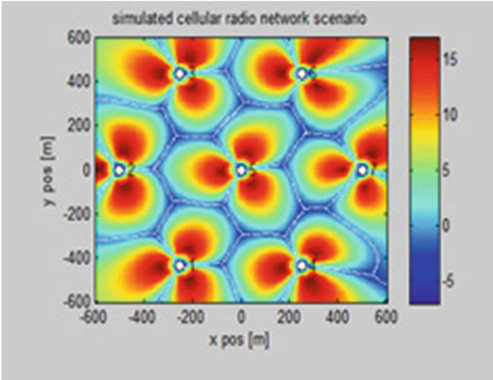


Fig. 10. Optimized network output (Color figure online)

7 Conclusion

This work focuses on the self-organizing networks in LTE to automate the configuration of the antenna parameter, azimuth angle. The proposed machine learning algorithm and researched parameter values help to learn the existing network and establish a relationship among the azimuth angles and PSS measure and thereby finding the azimuth tilts for which the PSS coordinates is minimum. The proposed method can be extended to incorporate various other parameters like power, frequency etc. to improve the optimization for the prevailing network. This is the advantage of the proposed algorithm which involves logical computations rather than technical changes in other parameters of the network.

8 Future Work

Our future work includes implementing the same algorithm in various other channel condition scenarios like cost231, Hata model etc. and make an analysis of the results. Future work also includes considering the configurable parameters other than azimuth angle such as vertical tilt, height of the base station from the ground, number of antennas that can be fired in the array etc. in implementing this machine learning algorithm.

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