Self-Configuration of antenna tilt of an LTE network by optimizing coverage holes area in the network

Kumar Yashashwi-Senior Undergraduate, Indian Institute of Technology (IIT) Bombay, Mumbai
Guide: Nikola Sucevic, Algorithms & Analytics - Data Science, Jio Coverage Platform, Reliance Jio Infocomm Ltd.

ABSTRACT

Providing ubiquitous network coverage is a goal of every telecom service provider. For this, the TSP should first be able to 'see' his network coverage as close to reality as possible. Various planning tools are available to predict the coverage of a network using standard RF propagation models. In this paper, we propose a method to enhance the prediction of coverage by using the available measurements of live network from users.

INTRODUCTION

Coverage of an area depends on various factors, some that are under operator's control and many beyond it. The onus is on the service provider to empower the user with a seamless connectivity despite these challenges. It is imperative that the service provider has a clear understanding about the network coverage on ground, rather than some predictions that miss out a lot of factors. A major differentiator of coverage is if the UE (User Equipment) is indoor or outdoor. Most of the prediction tools give the coverage plot of an outdoor environment while users stay indoors for major part. Distinction between indoor and outdoor is important because outdoor prediction paints an optimistic picture that might give a shock to the service provider when complaints start pouring in from users experiencing problem indoor.

MODEL TUNING

A radio wave propagation model is an empirical mathematical formulation for the characterization of radio wave propagation as a function of frequency, distance and other attributes. Path loss is the dominant factor for characterization of a radio link. Thus radio propagation models typically focus on realization of this parameter to model the distribution of signals, thus predicting area of coverage. Each individual telecommunication link has to encounter different terrain, path, obstructions, atmospheric conditions and other phenomena. This implies that it is not possible to formulate the exact path loss for all the telecommunication systems in a single equation. This is the challenge we are trying to address.

Okumara-Hata model is one of the most frequently used macroscopic propagation model. We have tuned this model for every site (eNodeB) based on the measured samples rather than going with single formula for every site. The coefficients in the equation are obtained for every site by curve fitting the measured samples. For this model, **path loss** is given by

$$\boldsymbol{PL = A + Blog(d) + C}$$

where A, B and C are the factors that depend on frequency and antenna height

$$A = 69.55 + 26.16\log(f_c) - 13.82\log(h_b) - a(h_m)$$

$$B = 44.9 - 6.55\log(h_b)$$

f_c *– carrier frequency in MHz*
d *– distance from antenna in km*
h_b *– height of base station*
h_m *– height of mobile station*

For the sake of simplicity, calculations are done on ground level. So, $a(h_m)$ term is ignored. Coverage prediction is done frequency wise. Thus, the equation is reduced to path loss as a function of distance from antenna and antenna height.

For 2300 MHz

$$\boldsymbol{Path\ Loss = 158.23 - 13.82\log(h_b) + (44.9 - 6.55\log(h_b))\log(d)}$$

All the coefficients above are obtained theoretically. We can replace them for every cell, based on its environment accordingly by curve fitting the measured samples to this equation format. This adds 'reality' to the propagation model. Once the path loss of a location is calculated and antenna gain model is known, coverage at the location can be predicted. The prediction can be further enhanced by having mathematical models of the cell for different angular spread.

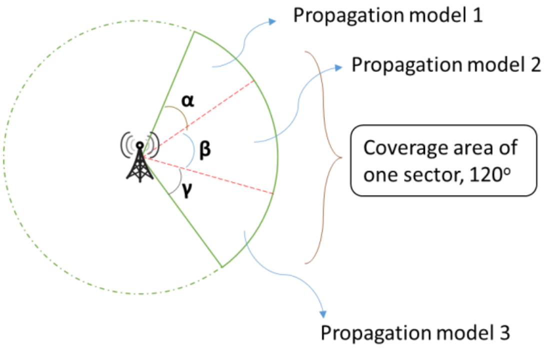

Figure1: Propagation models

In the above representation, coverage area of one cell is shown. Three propagation models are designed. One each for the sectors of angles **α, β**and**γ**. Each propagation model is obtained using the measured samples of the respective sectors. Once the path loss is obtained, Received signal reference power (RSRP) can be obtained.

RSRP CALCULATION

RSRP = Tx_power +Vertical gain +Horizontal gain -Pathloss

Vertical gain and horizontal gain of a point are dependent on vertical and horizontal angle respectively of the point with respect to antenna as in figure 2.

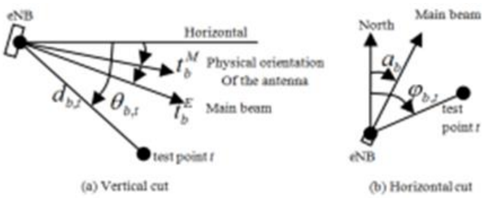

Figure 2: Vertical and Horizontal angles

Angle between the main beam vector and test point vector will determine the gain values. Prototype developed here is for vertical angle

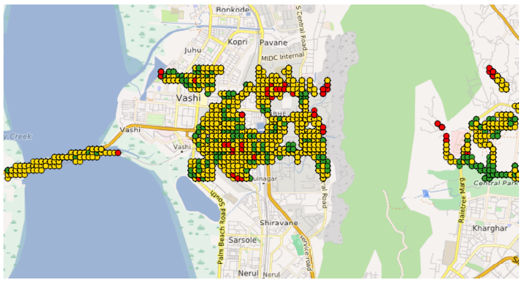

Figure 3: Initial RSRP for 2521 points

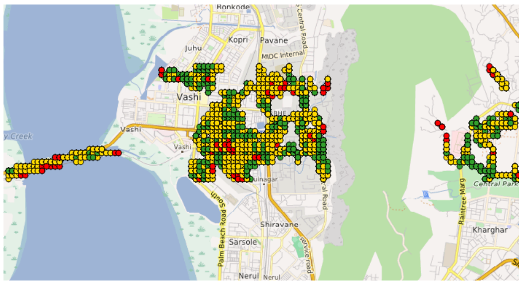

Figure 4: RSRP by 3 degree up-tilt to all antennas for same set of points

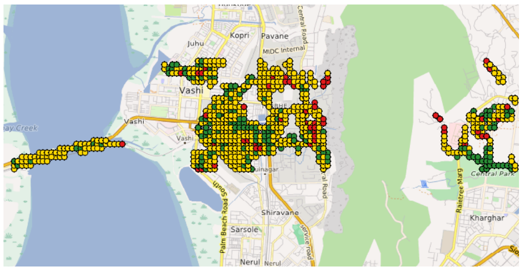

Figure 5: RSRP by 3 degree down-tilt to all antennas for same set of points

RSRP [-60dB —85dB]

RSRP [-85dB—105dB]

RSRP [< -105dB]

Figure 3 shows initial RSRP values as reported by the drive test data. Figure 4 and 5 are obtained by changing the antenna vertical tilt angle. As evident in figure 4 and 5, for some points the RSRP value has improved but for some it has deteriorated. Thus obtaining a combination of vertical angles for the antennas (some up and some down) coverage can be improved. For this purpose we use an optimization algorithm.

OPTIMIZATION

We rely on the generic technique of simulated annealing to solve the tilt optimization problem. For this purpose we need to formulate a cost function. Cost function used here is the area of coverage holes obtained by forming polygons around bad samples. Once the polygons are identified we calculate the total area of the coverage hole polygons and the aim is to minimize the area with minimum interference. Here we model the interference using G-factor defined as:

G-factor = a/(b*c)
a=RSRP of strongest eNB
b=RSRP of second strongest eNB
c=RSRP of third strongest eNB

Here G-factor puts a constraint while using the simulated annealing algorithm.

The technique in simulated annealing algorithm is an extended local search, where worse configurations regarding the cost function may also be accepted with certain probability (*p*) according to the so called Metropolis-test, in order to prevent the method to be trapped in a local minimum. Better solutions are always accepted ($p = 1$). Higher temperature values result in higher acceptance probability in case of a worse configuration.

The temperature decreases from an initial value (T_0) according to an annealing characteristic during the optimization. The initial temperature value should be chosen in such a way, that the acceptance probability of worse states should reach a relatively high value at the beginning of the optimization process. The equilibrium condition tells when the temperature can be decreased. If this condition is not satisfied, then the temperature does not change. The termination condition checks whether the optimization may stop or further iterations are needed. It can be based on observing the improvement of the cost function in the last few iterations, and if it is above a given limit the optimization terminates. Alternatively, a maximum iteration count can be defined as the termination condition. The steps of our proposed algorithm are the following:
1) Obtaining initial solution, α and initial temperature $T0$
2) C is the cost of α, C = total area of coverage holes), and let $C_{best} = C$ be the best solution found so far
3) Generating a new solution set $\alpha(1)'$,$\alpha(2)'$ ..., $\alpha(L)'$
• Randomly choosing one BS and configuring its antenna tilt in the surroundings of the current configuration
– i.e., +-2 degree antenna tilt is allowed in every iteration.
• Check G-factor constraint
– if G-factor obtained after change is less than initial G-factor then choose another configuration
• For each neighbor $\alpha(i)'$ configuration perform step 4 and 5
4) $C(i)$_ is the cost of the configuration $\alpha(i)'$
5) Metropolis-test: accept $\alpha(i)$_ as the current solution α with probability p
• $p = \exp[(C - C(i)')/T]$, if $C <= C(i)'$ (worse solution)
• $p = 1$, if $C > C(i)'$(better solution are always accepted)
• update $Cbest = C(i)'$, if there was an improvement in the cost function
6) Evaluating equilibrium condition (fixed iteration count was used)
• If not satisfied, do not change temperature and GOTO step 3
• If satisfied, update temperature and GOTO step 7
7) Evaluating back-step condition
• If in the last B steps (i.e., 50 iterations) C_{best} has not changed, then perform a back-step to a previous best configuration with uniform distribution (i.e., choose among the last 3 best configurations)
9) Evaluating termination condition (if maximal iteration count or minimal accept probability is reached)
• If it is not reached then GOTO step 3, otherwise
END

By performing a *random selection* (step 3) on the antennas and evaluating the cost function according to the *Metropolis test* (step 5) on neighbor configurations, a method which combines the advantages of simulated annealing and random walk search techniques can be obtained. The *back-step* (step 7) to a previous best configuration with uniform distribution when there was no improvement in the past *B* iterations reinforces the random walk nature of the method. As in this case the Optimization algorithm probably got to a wrong branch of the solution space, it can be meaningful to guide the algorithm toward a better direction with the back-step. During the neighbor generation only the narrow surroundings of a current configuration is considered in order to perform small changes in the state of the radio network which helps to preserve the stability of the method.

RESULT AND DISCUSSION

Upon evaluation of the discussed method we obtain the following result. The red colored area in figure 6,7 and 8 shows the coverage holes.

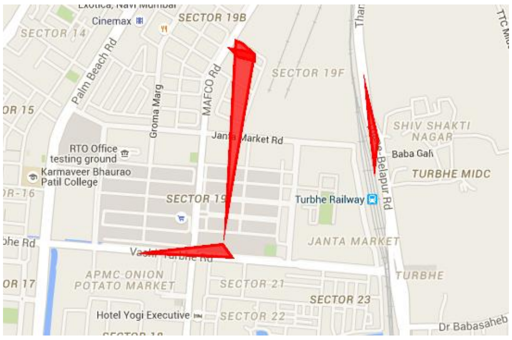

Figure 6: Initial coverage holes present (Total area = 36663.274117 m^2)

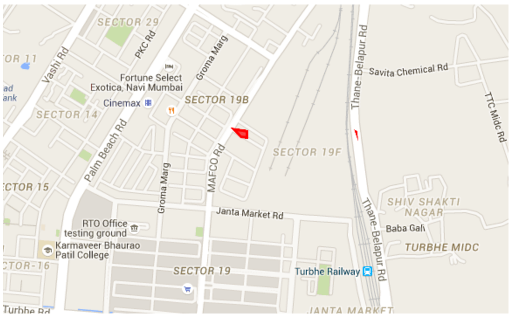

Figure 7: Coverage holes after 520 iterations (Total area = 1515.287453 m^2)

Figure 8: Coverage holes after 750 iterations (Total area = 444.303425 m^2)

In figure 6 we have the initial coverage holes. Figure 7 is an intermediate stage and figure 8 give the final coverage holes set (reduced to one in this case).On every iteration new set of tilt angles are obtained with area reducing with increasing iterations. Simulated annealing algorithm converges satisfactorily after 750 iterations reducing the area of coverage holes by a factor of nearly 100.

As discussed we had put a constraint on the optimization method. The interference among the eNodeBs in the area should be minimum.

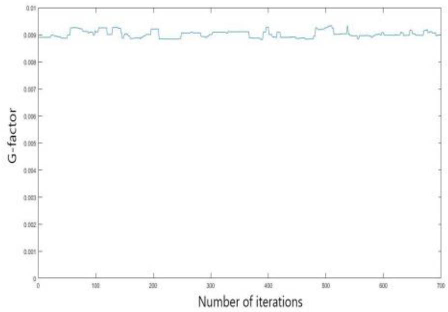

Figure 9: Plot:G-factor vs. No. of iterations

The G-factor remains nearly constant as we had placed a constraint on it while choosing the new set of tilt angles.

FURTHER ENHANCMENTS

The above prototype is developed only for vertical tilt angle. But the same method can be applied to obtain optimized set of horizontal angle, transmitted power and even height.

CONCLUSION

In this paper we have proposed an optimization framework which is based on regular terminal measurements instead of specialized test measurements to track the state of the radio. Results have shown, that choosing antenna tilts according to the straightforward geometry based setting results in very poor overall performance, while our proposed method based on the simulated annealing technique finds comparable solutions to the one obtained by an exhaustive search and it remains applicable for larger networks as well, where the exhaustive search would be infeasible.

ACKNOWLEDGEMENT

I would like to thank Mr. Nikola Sucevic for guiding and providing valuable suggestions during the course of my project. I would also like to thank Mr. Prashanth Gonti and Mr. Abhilash Acharya of JCP Data Science team for helping me throughout the project.