

Automation of Millimeter Wave Network Planning for Outdoor Coverage in Dense Urban Areas Using Wall-Mounted Base Stations

Nima Palizban, *Student Member, IEEE*, Sebastian Szyszkowicz, *Member, IEEE*, and Halim Yanikomeroglu, *Fellow, IEEE*

Abstract—The millimeter wave (mmWave) spectrum is an important candidate band for next-generation cellular networks. Using higher frequencies, mmWaves are much more sensitive to blockage, and the presence of line-of-sight links is more desired, making the network planning more dependent on the layout of the cities. In this letter, we use computational geometry and optimization tools to fully automate the process of planning an outdoor mmWave network in dense cities, using wall-mounted below-rooftop base stations (BSs). Based on the locations found, one can analyze some properties of mmWave networks. We provide information about the BS density and coverage in two different large urban areas.

Index Terms—Network planning, mmWave, base station density, 5G, maximum coverage problem.

I. INTRODUCTION

THE WIRELESS data streaming expansion in recent years suggests that the 5G networks will need to support substantially higher rates [1]. One of the key enabler technologies for providing such a high capacity is increasing the bandwidth assigned to each cell [2]. Congestion in current ultra high frequency (UHF) bands has drawn much attention to using the millimeter wave (mmWave) spectrum. Using higher frequency mmWave bands can provide us with approximately 200 times more bandwidth than the currently occupied spectrum for mobile communications [3]. There are two main challenges in using mmWaves. First, a mmWave network needs to use highly directional antennas to overcome path loss. Second, mmWaves are very sensitive to blockage [1], [2], with important consequences for the channel model.

Due to the much smaller wavelength of mmWaves compared to other objects in the map, diffraction is negligible. It is seen in [4] that for many common materials the penetration loss is very high, which leads to a significant isolation of indoor and outdoor areas and emphasizes the role of line-of-sight (LOS) links. As a result of the building blockage, the coverage area will be highly dependent on the layout of the city. Furthermore, cell shape will be more affected by blockage

rather than distance [1], which affects the network planning and emphasizes the need to accurately model the blockage as well as base station (BS) locations [5].

Some model the buildings as randomly sized rectangles placed randomly [6]. Also, some include real maps to analyze the coverage and rate trends, using uniformly distributed BSs [7]. Some approximate the non-LOS/LOS regimes using a multi-ball model [5], [8], which approximates the LOS probability with a piecewise function of distance from the BS.

In this letter, we plan the below-rooftop wall-mounted base station (WMBS) locations on real maps, so as to give coverage to the outdoor area of a city. We use computational geometry and optimization tools to plan the network, using the simplified LOS coverage model. We further present statistical information regarding BS density, coverage, and signal-to-interference-plus-noise-ratio (SINR) in different city layouts.

II. PROBLEM STATEMENT

We consider 2D network planning with WMBSs to cover the outdoor areas. We place no constraints on the height of the WMBSs; however, because of the outdoor obstacles, higher BSs would be preferred [9]. We assume a cell radius of 200 m, as in [4], and only consider LOS coverage [10]. We do not take into account interference in the network planning algorithm, as it is expected to be much less significant than in current networks [1], [11]. Instead, we focus on optimizing LOS area coverage, which may be the limiting factor in mmWave networks [1]. We take map data from the OpenStreetMap project, which is open-source and regularly updated [12].

BS placement is divided into two steps: first, we identify many potential locations according to the algorithm in [13], which is briefly explained in Section II-A; second, we choose a small subset of the BS candidate locations to maximize the outdoor coverage, which is the purpose of this letter.

A. Identifying Potential BS Locations

In this section, an overview of [13] is given. After extracting the map data, adjacent buildings are merged and the holes inside them are removed to form simple polygons (SPs). Then we assign a cell to each SP such that the points in the cell are closest to that SP. Two SPs are called natural neighbours (NNs) if their associated cells touch. One can define a link between any pair of NNs to be the shortest line segment connecting their SPs. According to these links, each SPs contour is partitioned into a number of regions. Each region is then explored

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The authors are with the Department of Systems and Computer Engineering, Carleton University, Ottawa, ON K1S-5B6, Canada (e-mail: nimapalizban@sce.carleton.ca; sz@sce.carleton.ca; halim@sce.carleton.ca).

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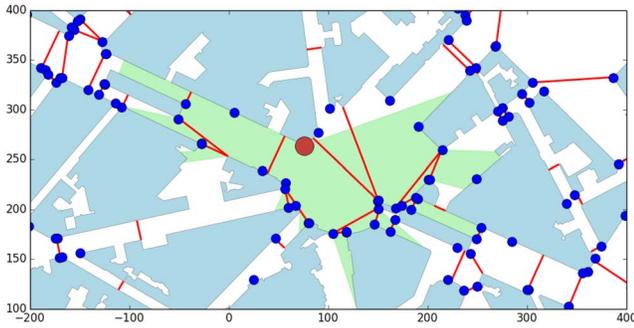


Fig. 1. Results of algorithm in [13] for identifying many good BS candidate locations. Light blue areas are the city blocks found from merging the city buildings and removing the holes. Red lines are the shortest links between natural neighbour buildings. Blue points are candidate locations to cover outdoor street area (white area in the map). One candidate BS location is chosen randomly (large red circle) with its LOS coverage area in green.

to find a point with maximum LOS area and that point is considered as a potential candidate location. Fig. 1 illustrates this algorithm.

B. Network Planning With a Subset of Candidate BSs

Now that we have many potentially good locations for placing BSs, the objective is to choose a small subset of these candidate BSs to maximize the area covered by them. We model the area by placing grid points (with equal weight) on the map, such that each point represents a small square area. The LOS region covered by each candidate BS location is known. We then formulate the problem to cover as many points as possible using a subset of the candidate BSs.

III. SOLUTION

The problem is approached in two different ways: in Section III-A, we give a heuristic solution, based on greedy addition (GA). Then, in Section III-B, the problem is formulated as a maximum coverage problem (MCP) and binary integer linear programming (BILP) is used to solve it. Finally, in Section III-C, remarks are given about the optimality of the solution and convex linear programming (CVLP) is used to bound the performance of these methods.

A. Greedy Addition

At first, we use a heuristic approach to approximate a solution for this problem. We start with a number k of BSs to place. The main idea is to divide the problem into steps, and in each step choose the best BS location, then update the points to be covered and repeat all this k times. The GA can be formulated as follows:

- If k is zero, end.
- Choose the best candidate BS location (one that covers the largest number of points) and place a BS there.
- Remove all of the points covered by that BS.
- Assign $k \leftarrow k - 1$ and go to the beginning.

The GA needs more BSs to cover the same amount of area than the optimal algorithm, but its coverage area is guaranteed to be at least $(1 - 1/e) \approx 0.63$ of the optimal

solution's area with the same number of BSs [14]. The GA is a polynomial-time problem and is shown in [15] to be the best polynomial-time approximation for finding the solution of the MCP. Moreover, the GA is simple to implement and scales easily for larger maps.

B. Binary Integer Linear Programming

We define the vector z to be a vector of n binary variables, where n is the total number of points distributed in outdoor areas. z is the state of all distributed points, that is $z_j = 1$ if the point j is covered and $z_j = 0$ otherwise. We define a vector y to be a vector of m binary variables, where m is the total number of candidate locations; $y_i = 1$ if a BS is placed in candidate location i and $y_i = 0$ otherwise. All the coverage information of the points and candidate locations is summarized in the matrix M :

$$M = [m_{ij}]_{m \times n}, \quad m_{ij} \in \{0, 1\}, \quad (1)$$

where $m_{ij} = 1$ if the point j is covered by the candidate BS location i , and $m_{ij} = 0$ otherwise. Having this information, the MCP can be written as the following BILP:

$$\text{maximize} \quad \sum_{j=1}^n z_j, \quad (2)$$

$$\text{subject to} \quad \sum_{i=1}^m m_{ij} y_i \geq z_j, \quad j \in \{1, \dots, n\}, \quad (3)$$

$$\sum_{i=1}^m y_i = k, \quad (4)$$

$$z_j \in \{0, 1\}, \quad j \in \{1, \dots, n\}, \quad (5)$$

$$y_i \in \{0, 1\}, \quad i \in \{1, \dots, m\}. \quad (6)$$

If point j is covered ($z_j = 1$), at least one of the candidate BSs covering it should be deployed, giving constraint (3). We want to use k BSs in total, so the summation over y should be k , giving (4). The number of points covered can be found by a summation over z , giving the objective function (2).

The MCP is NP-hard [15]. Using BILP, it takes much more computational time than GA.

C. Bound via Convex Linear Programming

Since the MCP is modeled as a BILP, it may be hard and time-consuming to find the optimal solution. In this section, we maximize the objective function using the relaxation method.

The only constraints that make the problem non-convex are constraints (5) and (6). By relaxing them to (7), the problem is transformed to a CVLP:

$$0 \leq z_j \leq 1, \quad 0 \leq y_i \leq 1, \quad \forall i, \quad \forall j. \quad (7)$$

In most cases, some of the values of y_i or z_i will be fractional, which does not correspond to a feasible solution but does give an upper bound of the solution [16].

In contrast to the BILP, which is an NP-hard problem, the CVLP can be solved in polynomial time.

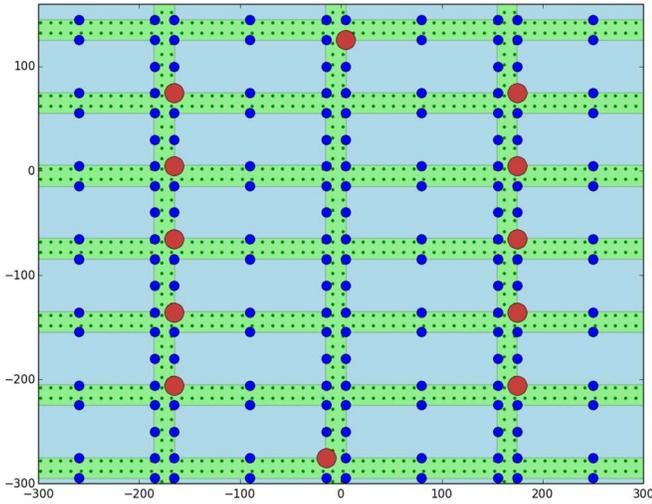


Fig. 2. Regular grid map: Blocks are $150\text{ m} \times 50\text{ m}$ sized, and streets are 20 m wide. Blue points are candidate locations, placed on corners and middles of block sides, large red points are BILP-chosen locations for BSs, and the point grid represents user locations in the optimization formulations. When we want to cover all the area (in green), the algorithm selects the corner points, showing that placing BSs on corner points is a sensible strategy.

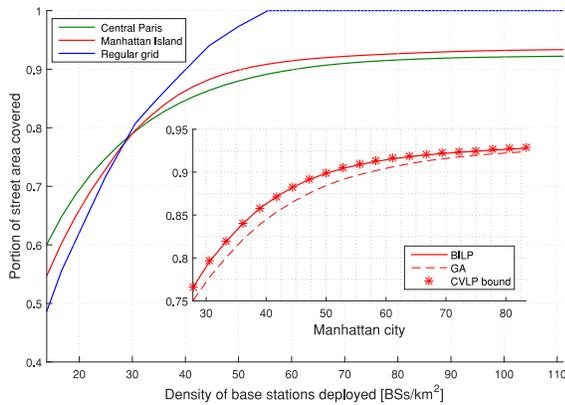


Fig. 3. BS density for different cities using BILP: The mean value of 28 maps of central Paris and 10 maps of Manhattan Island. The inner figure compares the GA, BILP and CVLP bound for Manhattan Island.

IV. SIMULATION RESULTS

Using the algorithm in [13] and the formulation in this letter, we plan the network on several maps of Paris and Manhattan taken from the OpenStreetMap project [12]. Map locations are summarized in Table I. We also use a regular grid map (Fig. 2) to make the results easily reproducible.

For all of the maps, we plan the network with the GA and BILP with a varying number of BSs. Then we record the number of covered points and find the coverage percentage: Fig. 3 depicts the outdoor coverage area percentage as a function of BS density. The beginning sharp slope for Paris is due to large open areas in the city; later, because of narrow and bending streets, the slope goes down dramatically. Meanwhile, in regular grid map and Manhattan Island, the slope does not change as drastically. For reasonable coverage (90%), the cities with long straight and regular streets need smaller BS density. We found 40, 50, and 60 BSs/km² densities to cover 90% outdoor area in regular grid, Manhattan Island, and Central Paris,

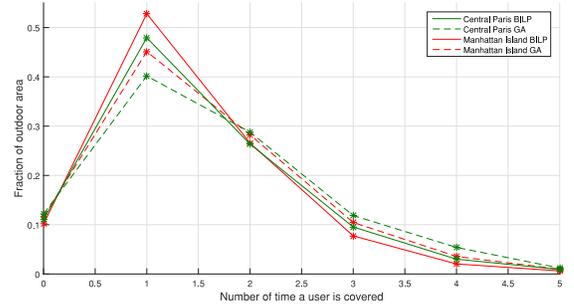


Fig. 4. Number of times a certain area is covered, for 90% outdoor coverage. A typical outdoor user is covered by about 1.5 BSs on average, meaning that the number of strong interferers (both LOS and within 200 m) is about 0.5 on average. There are almost never more than 3 strong interferers.

TABLE I
SIMULATION SETUP AND RESULTS SUMMARY

Urban area	South Manhattan	Central Paris
Centre	73.9865° W, 40.7468° N	2.334° E, 48.8600° N
Number of maps	2 × 5	7 × 4
Map size	1 km × 1 km	1 km × 1 km
Area studied	600 m × 600 m	600 m × 600 m
User grid spacing	10 m	10 m
LOS area within		
50 m	$\hat{\mu} = 48.3\%$, $\hat{\sigma} = 11.7\%$	$\hat{\mu} = 33.6\%$, $\hat{\sigma} = 14.7\%$
100 m	$\hat{\mu} = 28.1\%$, $\hat{\sigma} = 9.9\%$	$\hat{\mu} = 19.1\%$, $\hat{\sigma} = 12.4\%$
150 m	$\hat{\mu} = 19.0\%$, $\hat{\sigma} = 8.3\%$	$\hat{\mu} = 12.8\%$, $\hat{\sigma} = 10.3\%$
200 m	$\hat{\mu} = 14.1\%$, $\hat{\sigma} = 6.8\%$	$\hat{\mu} = 9.37\%$, $\hat{\sigma} = 8.63\%$
Parameters	Meaning	Value
P_{tx}	transmit power	30 dBm
G_s	serving link antenna gain	16 dBi
G_i	interfering link antenna gain	5 dBi
W	downlink bandwidth	500 MHz
N_0	thermal noise	-174 dBm/Hz
F	noise figure	7 dB
$L_L(d)$	LOS path loss	$61.4 + 20.0 \log_{10}(d)$ dB
$L_N(d)$	non-LOS path loss	$72.2 + 29.2 \log_{10}(d)$ dB
	d : 3D distance in meters	
$h_{BS} - h_M$	propagation height difference	15 m - 1.5 m

respectively. On average, the GA places 16% more BSs than BILP. Also, CVLP leads to a tight density bound, its maximum difference with the BILP solution being less than 4% more density.

Fig. 4 shows the number of BSs within 200 m that a user can see, and consequently the number of strong interferers. We observe about 0.5 strong interferers on average and rarely more than 3. These results are based on city geometry and will not change with frequency or antenna configuration.

Based on all collected data from the chosen BSs, the distribution of the fraction of LOS inside a disc is calculated, with mean ($\hat{\mu}$) and variance ($\hat{\sigma}^2$) values reported in Table I. In Manhattan Island, for a 200 m radius, the average LOS coverage is 14.1%, which is higher than the 11% LOS coverage reported in [13] and [17], which shows the benefit of choosing good BS locations.

Finally, we evaluate the downlink SINR of the planned networks, which is given by

$$\gamma = \frac{G_s}{L_L(d_0)} \left(\sum_j \frac{G_i}{L_L(d_j)} + \sum_k \frac{G_i}{L_N(d_k)} + \frac{WN_0F}{P_{tx}} \right)^{-1} \quad (8)$$

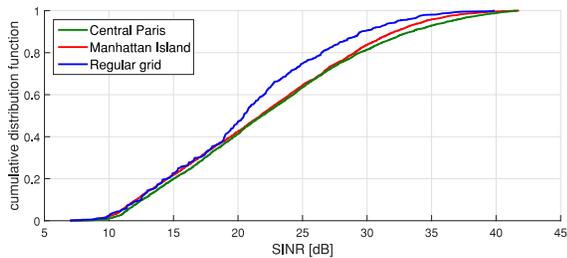


Fig. 5. The empirical SINR distribution for mmWave networks planned on different city types, for 90% area coverage.

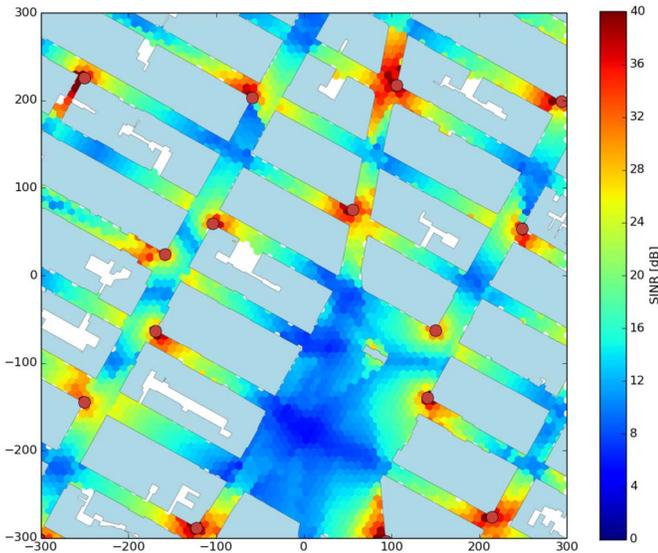


Fig. 6. Result of the BILP planning with 50 BSs on a 1km^2 Manhattan Island area, with its corresponding spatial SINR distribution. The SINR is calculated in the inner $600\text{ m} \times 600\text{ m}$ area to avoid edge effects: 16 BSs can be seen in this area. White regions do not have a serving LOS link and are considered in outage.

where d_0 is the distance to the closest BS, and $\{d_j\}$ and $\{d_k\}$ are the sets of distances to the LOS and non-LOS interfering BSs, respectively. The other parameters are based on [11] and are given in Table I. We only consider signal links that have LOS, since non-LOS coverage needs more accurate models and ray-tracing [2] analysis. We still considered non-LOS interferers, so as to not under-estimate the interference.

Fig. 5 shows the empirical SINR distribution per city. The median value of the SINR distribution is around 22 dB, which demonstrates the good performance of the planned network. In [8], mmWave SINRs are also estimated according to [11], but with more optimistic antenna gains. Correspondingly, higher SINRs were obtained (≈ 30 dB at 28 GHz). Fig. 6 shows a particular SINR map, where the effect of street geometry on the spatial distribution of the SINR can be seen.

V. CONCLUSION

Cell planning according to LOS coverage can be done using computational geometry and optimization tools. We automated the mmWave network planning over a large area of open map data to find BSs densities for LOS coverage and SINR distributions in outdoor dense urban areas. We find different BSs densities according to city layouts, which emphasizes the benefit of using realistic map data analysis.

Given the network planner and BSs densities, one can further analyze the properties of mmWave cells and networks. Future work may also consider more accurate coverage analysis (including good non-LOS regions) using ray-tracing tools for an even more realistic network assessment.

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