Vehicles or Pedestrians: On the gNB Placement in Ultradense Urban Areas

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***Abstract*—This paper tackles the problem of base stations placement to guarantee line of sight connectivity to vehicles in urban areas, when high frequency communications (mmWave or TeraHertz) are used. Our novel methodology takes advantage of vehicular traffic simulation to generate a realistic demand model for vehicles in urban areas. Then, through a bounded error heuristic, find the maximal coverage that can be achieved with a given density of base stations. The heuristic is implemented on GPU and used to evaluate the coverage in a densely urbanized area in the city of Luxembourg. Our results indicate that a reasonably low density (20 base stations per km²) is sufficient to provide coverage for vehicles in urban environments. However, optimizing solely on vehicles negatively affects the coverage of pedestrians.**

***Index Terms*—vehicular communication, 5G, mmWave, gNB placement**

I. Introduction and State of the Art

In order to meet the increasing demand for mobile connectivity, the next-generation access networks (which we refer to as XG) will rely on the use of very high frequencies (mmWave and TeraHerz) and on the densification of the existing access network, by increasing up to 10 times the number of base stations deployed [1]. These new communication technologies are much more susceptible to obstruction and they need Line-of-Sight (LoS) to function reliably. For these reasons, the placement strategy of base stations is crucial, and as already shown in previous works, an optimal choice of such locations can lead to substantial savings for network operators [2].

One of the future application enabled by XG is the use of Cooperative Autonomous Vehicles (CAVs). To be really effective, cooperative driving will not only require vehicles to exchange basic data such as position, speed, heading, etc., but raw sensor data as well. This will permit vehicles to implement Cooperative Perception (CP) [3], i.e., to be able to construct a view of the surrounding environment that goes beyond the field of view of their sensors. Sharing raw sensor data rather than pre-processed data enables vehicles to take decisions on their own or to come up with a consensus on how to classify certain objects, which can lead to safer and more efficient driving (see the *boar and the hare* example [4]).

While the placement of base stations is a widely investigated matter [5], the LoS requirements introduced by the newer communication technologies have reignited the attention on the subject, with several works taking advantage of similar techniques [6]–[9]. However, to the best of our knowledge, no other study is focused on investigating different placement strategies to optimize mobile coverage for vehicles using realistic traffic data. The most similar research, from Jaquet et al. [10] is focused on enhancing vehicular networks by taking advantage of unmanned aerial vehicles.

This paper improves a recently-introduced 3D approach to find an optimal placement for gNBs (the name for the base stations in the 5G standard) by taking into account the traffic patterns in order to better cover the areas where there is a high vehicular traffic. First, we derive a demand model by using simulated traffic data, then we devise a new heuristic that takes advantage of the demand model to find the optimal location of the gNBs. We take advantage of open geographical data, specifically OpenStreetMap (OSM) vectorial maps and Digital Surface Model (DSM) to evaluate different gNB placements on real-world data. While the analyses have been conducted only in the city of Luxembourg, the availability of open-data together with the source code we release will enable anyone else to reproduce the analyses in different areas.

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II. Problem Formulation

Given a 3D shape of an urban area, we identify a set of points Λ in the ground that can be potentially covered with a LoS connection from a gNB. Each point corresponds to an (x, y, z) triplet, in which the (x, y) coordinates are quantized using one point per squared meter. Points are selected to be outside any building shape and only in public areas (streets, roundabouts, street parking, sidewalks) and not in private areas. The problem we tackle can be summarized in three steps described in the next two sections:

1) For each point define a weight, the higher the weight the higher the probability the point will be covered.
2) Identify the set P of points in space in which a gNB could potentially be placed. Each position p_i is defined by an (x, y, z) triplet, and we restrict our analysis to the facades of buildings.
3) Find an algorithm that chooses the minimal number of gNB so that the coverage is maximized.

Step one is a novel contribution of this paper. The solution to the second step comes from a previous publication in which we introduced the problem of coverage as a variation of the classical maximum subset coverage problem [2], the third step modifies the solution proposed therein to take into account the weights introduced in step one.

III. A Demand model for Vehicles

Obtaining realistic vehicular traffic data is always a challenging task, as data collected by cities is rarely released to the public. One possibility, which is the one we consider in this work, is to generate traffic data using microscopic traffic simulators and realistic scenarios. In this work we use the urban traffic simulator SUMO [11] to generate realistic mobility traces of the city of Luxembourg. In particular, we make use of the Luxembourg SUMO Traffic (LuST) scenario [12], a publicly available scenario generated from traffic data provided by the Luxembourg government which includes both public and private transportation over a period of 24 h.

To obtain traffic traces, we run the scenario over the full 24 h for a total of 286 215 vehicles moving on the streets. The simulation step is set to 1 s and, at the same frequency, we log the positions of the vehicles in the area of the city shown in Fig. 1, corresponding to roughly $4\,\mathrm{km}^2$. We collect traces using GPS (latitude/longitude) coordinates and then convert them to a `.gpx` file for later processing.

To generate a matrix of weights from these traces, we first rasterize the traces mapping each logged position to a cell of a matrix, where a matrix cell represents an area of $1\,\mathrm{m}^2$. We obtain a matrix $\boldsymbol{\tau}^\star$ where $\boldsymbol{\tau}^\star_{x,y} = n$ means that n vehicles have passed from the (x, y) cell during the whole simulation. For the sake of readability we rescale it to the number of passages per minute. Fig. 3 shows the empirical pdf of the values of the cells with non zero value, binned with bins of size 0.125 passages/minute. It can be seen that the majority of the cells have less than one passage per minute, with the 95th percentile roughly at 0.55. The distribution is pretty skewed, with about 5 orders of magnitude between the largest and the lowest frequency.

For reasons that will be clear in the next section, Eq. (1) remaps the values to an `uint8` type in the range $[0, 255]$ obtaining the traffic matrix $\boldsymbol{\tau}$. The values up to the 95th percentile have been linearly mapped in the interval $(0, 64)$, while the rest of the values have been linearly mapped to the range $(64, 255)$. Note that we have considered the values greater than 21 as outliers and thus they are all equally mapped to 255.

$$\boldsymbol{\tau}_{x,y} = \begin{cases} \lceil 116 \cdot \boldsymbol{\tau}^\star_{x,y} \rceil & \text{if } \boldsymbol{\tau}^\star_{x,y} \leq 0.55 \\ \lceil 9.34 \cdot \boldsymbol{\tau}^\star_{x,y} + 58.77 \rceil & \text{if } 0.55 \leq \boldsymbol{\tau}^\star_{x,y} \leq 21 \\ 255 & \textit{otherwise} \end{cases} \tag{1}$$

IV. gNB Placement

The second required step is to define the set of candidate locations P from which we will choose the positions of the gNBs. Let $\mathcal{B} = \{b_i\}$ be the set of buildings extracted from the OSM dataset. Let also $\phi(b_i)$ be a function that extracts a set of coordinates that compose the perimeter of the building b_i, with points spaced in average one meter away from each other,

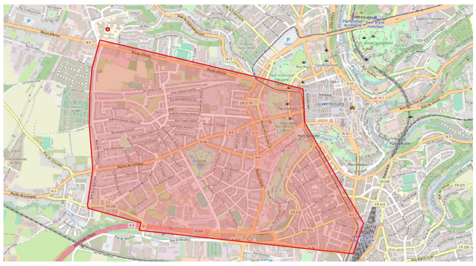

Fig. 1: Area of the city of Luxembourg over which traces are collected.

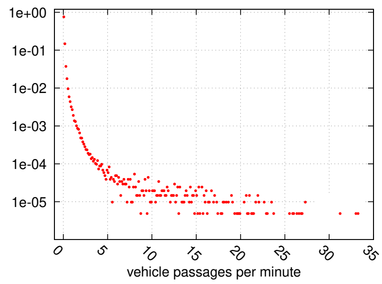

Fig. 2: Empirical p.d.f. of the vehicles passages per minute per cell.

placed 1m below the height of the roof. We can then define the set of candidate locations $\mathcal{P}$ as:

$$\mathcal{P} = \bigcup_{b_i \in \mathcal{B}} \phi(b_i) \tag{2}$$

Once the set of candidate locations is determined, we need to evaluate the coverage from each one of them. In order to do so, we take advantage of a viewshed algorithm implemented using the CUDA library on NVidia GPUs [13]. This algorithm, applied on a highly precise DSM computes the presence of LoS from the candidate location p_i to each point in Λ given a maximum distance ($d_{max} = 300\,\mathrm{m}$) from p_i. Let $\boldsymbol{\sigma}^i = \Upsilon(\boldsymbol{\Lambda}, p_i)$ be a 2-dimensional binary matrix that associates each point in (x, y) to a non-zero value if there is LoS from the point p_i to the point of coordinate $(x, y, z) \in \Lambda$. Υ corresponds to the application of the viewshed algorithm from the point p_i over the set of points Λ. We call $\boldsymbol{\sigma}^i$ the *viewshed* matrix from point p_i. If we apply Υ to all the points in P we obtain a collection of matrices that represent all the possible viewsheds from all the potential positions of gNBs, as in Eq. (3):

$$\Omega = \bigcup_{p_i \in \mathcal{P}} \Upsilon(\boldsymbol{\Lambda}, p_i) \tag{3}$$

We then obtain a collection of matrices $\Omega = \{\boldsymbol{\sigma}^1, \boldsymbol{\sigma}^2, \ldots, \boldsymbol{\sigma}^m\}$ in which $\boldsymbol{\sigma}^i_{x,y} = 1$ means that a terminal in position (x, y) has LoS with a gNB placed in the point p_i.

A. Quasi-optimal gNB placement

We want to find a subset $\Omega^\star \subseteq \Omega$ whose size is lower than a parameter k ($|\Omega^\star| \leq k$) that maximises the elements coverage $\left|\bigvee_{\sigma^i \in \Omega^\star} \sigma^i\right|$, where $\bigvee$ is the OR operator between binary matrices and $|\cdot|$ is the norm-1 operator (the sum or all elements). In order to take into account the traffic patterns, let $\boldsymbol{\tau}$ be a non-negative integer matrix as defined in Eq. (1) with the same shape of $\boldsymbol{\sigma}^i$. We can formulate the maximization objective as follows:

$$\max_{\Omega^\star} \left| \boldsymbol{\tau} \odot \bigvee_{\boldsymbol{\sigma}^i \in \Omega^\star} \boldsymbol{\sigma}^i \right| \tag{4}$$

Where $\odot$ is the element-by-element multiplication between two matrices. This will lead to a choice of the optimal k sets in $\Omega^\star$ to cover the roads with the highest traffic. The problem is a so-called weighted maximum coverage problem.

We can now better justify Eq. (1). Since the frequencies in Fig. 3 are very skewed, and we are using a GPU with integer algebra, we can not remap linearly between 1 and 255, or else, 95% of the samples would be squashed at weight 1. On the other hand we want to give a strong priority to points with a very high weight, so we decided to linearize the weights with two different slopes. This guarantees that our heuristic will choose the few points with a high weight with a high priority, but also that it will be able to distinguish between points with low, but different weights.

Note that if we call $\mathbb{1}$ the matrix made of all one elements, and we set $\boldsymbol{\tau} = \mathbb{1}$ then the problem converges to the classical unweighted maximum coverage problem, in which we try to cover the largest portion of the points in Λ treating all of them equally. In other words, the weighted variant tries to optimize the coverage of cars, while the unweighted variant tries to optimize the coverage of all terminals in the public areas, streets, crossroads, sidewalks, and thus can be interpreted as the attempt to provide coverage to pedestrians, for which we can not have a movement pattern.

While this heuristic solution either optimizes the coverage for vehicles or pedestrians, a future extension of this work could consider a mixed objective between vehicles and pedestrians, which could improve the coverage of pedestrians in a vehicle-oriented network. For example, a different mapping function (Eq. (1)) could assign a minimal coverage priority to all the cells where no vehicles had passed.

B. Heuristic solution

Since the above-described coverage problem is NP-Hard in our past work we relied on a polynomial greedy heuristic with bounded error to efficiently find a quasi-optimal solution [2].

Here we modify the greedy heuristic as described in detail in Algorithm 1 to take into account the weight provided by the vehicular networks simulations. The heuristic proceeds as follows: we start by defining a coverage matrix $\mathbf{C}$ of the same size of $\boldsymbol{\tau}$, initialized with zeroes (Line 2). Each iteration of the loop in Line 4 will choose the position of one gNB. For each candidate location p_i and the corresponding viewshed $\boldsymbol{\sigma}^i$ we derive the so-far uncovered elements as the negation of the coverage matrix (Line 7). We define $\mathbf{C}^\star$ that represents the so-far uncovered elements that would be covered by the candidate location, with their weight given by $\boldsymbol{\tau}$ (Line 8). Note that $bool()$ is a function that makes an integer matrix a boolean one, $\neg$ is the boolean NOT operand. We then provide a score for p_i as the norm-1 of the coverage matrix (in Line 9). Then, the element with the maximal ranking is chosen and the corresponding values of the viewshed matrix are added to $\mathbf{C}$ (Line 12). Note this makes $\mathbf{C}$ a non-boolean matrix. Finally, the viewshed $\boldsymbol{\sigma}^\star$ is added to the set of optimal viewsheds (Line 13). The loop is repeated till the number of desired locations is reached. The operation at line Line 8 has complexity $|\Lambda|$, and is repeated at most $k \times m$ times, so the overall complexity is $O(km|\Lambda|)$.

The result of this algorithm is a set of quasi-optimal viewsheds.

Algorithm 1 Greedy algorithm for the weighted maximum coverage problem.

Require: Ω (Set of viewsheds), k (number of gNBs), $\boldsymbol{\tau}$(weighted traffic matrix)
Ensure: $\Omega^\star$ (Set of the viewsheds from optimal locations)

1: **procedure** $\Gamma(\Omega, k, \boldsymbol{\tau})$
2: $\quad \mathbf{C} = \mathbf{0}$
3: $\quad \Omega^\star = \{\}$
4: $\quad$ **for** $i \leftarrow 0$ to k **do**
5: $\quad\quad h^\star = -\infty$
6: $\quad\quad$ **for** $\boldsymbol{\sigma}^j \in \Omega$ **do**
7: $\quad\quad\quad \bar{\boldsymbol{C}} = \neg bool(\mathbf{C})$
8: $\quad\quad\quad \mathbf{C}^\star = \bar{\boldsymbol{C}} \odot \boldsymbol{\sigma}^j \odot \boldsymbol{\tau}$
9: $\quad\quad\quad h_j = |\mathbf{C}^\star|$
10: $\quad\quad\quad$ **if** $h_j > h^\star$ and $\boldsymbol{\sigma}^j \notin \Omega^\star$ **then**
11: $\quad\quad\quad\quad \boldsymbol{\sigma}^\star = \boldsymbol{\sigma}^j; h^\star = h_j$
12: $\quad\quad \mathbf{C} = \mathbf{C} + \boldsymbol{\sigma}^\star$
13: $\quad\quad \Omega^\star = \Omega^\star \cup \{\boldsymbol{\sigma}^\star\}$
14: $\quad$ **return** $\Omega^\star$

V. Experiments and Results

Our initial results are based on a single area in the city of Luxembourg with a surface S of roughly 4km^2.

We apply Algorithm 1 to compute the optimal locations for the gNBs, increasing k. We consider a density λ of gNBs per squared km going from 5 to 85 at steps of 5, and we set $k = \lambda S$. We consider two different settings, one in which we use the weighted variant, and another in which we use the unweighted variant ($\boldsymbol{\tau}_{x,y} = 1$) so every element in Λ has the same weight. We obtain two solutions for the coverage

$$\Omega^\star_{\lambda,\boldsymbol{\tau}} = \Gamma(\Omega, \lambda * S, \boldsymbol{\tau}) \tag{5}$$
$$\Omega^\star_{\lambda,\mathbb{1}} = \Gamma(\Omega, \lambda * S, \mathbb{1}) \tag{6}$$

that we aggregate with the OR operator to obtain a full coverage matrix:

$$\Phi_{\lambda,\boldsymbol{\tau}} = \bigvee_{\boldsymbol{\sigma}^j \in \Omega^\star_{\lambda,\boldsymbol{\tau}}} \boldsymbol{\sigma}^j; \quad \Phi_{\lambda,\mathbb{1}} = \bigvee_{\boldsymbol{\sigma}^j \in \Omega^\star_{\lambda,\mathbb{1}}} \boldsymbol{\sigma}^j \tag{7}$$

Finally, we use four metrics to compare the results:

$$Vcov_{\boldsymbol{\tau}}(\lambda) = \frac{|\boldsymbol{\tau} \odot \Phi_{\lambda,\boldsymbol{\tau}}|}{|\boldsymbol{\tau}|}; \quad Vcov_{\mathbb{1}}(\lambda) = \frac{|\boldsymbol{\tau} \odot \Phi_{\lambda,\mathbb{1}}|}{|\boldsymbol{\tau}|} \tag{8}$$

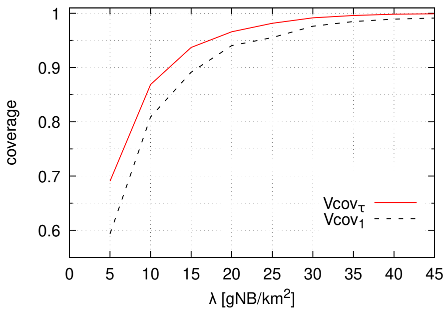

Fig. 3: The $Vcov_{\boldsymbol{\tau}}$ and $Vcov_{\mathbb{1}}$ metrics.

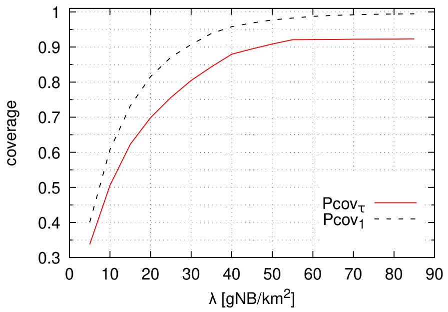

Fig. 4: The $Pcov_{\boldsymbol{\tau}}$ and $Pcov_{\mathbb{1}}$ metrics.

The metrics in Eq. (8) tell how good is the coverage of vehicles when we optimize for vehicles ($Vcov_{\boldsymbol{\tau}}(\lambda)$) or when we optimize for pedestrians ($Vcov_{\mathbb{1}}(\lambda)$). The second metric, in practice, tells us what happens if we try to optimize the street coverage for pedestrians but we measure the results only on the points where the vehicles pass (with their multiplicity).

$$Pcov_{\boldsymbol{\tau}}(\lambda) = \frac{|\Phi_{\lambda,\boldsymbol{\tau}}|}{|\Lambda|}; \quad Pcov_{\mathbb{1}}(\lambda) = \frac{|\Phi_{\lambda,\mathbb{1}}|}{|\Lambda|} \tag{9}$$

Metrics in Eq. (9) instead are used to evaluate the opposite situation. Both metrics express how good is the coverage of pedestrians, in the first case when we optimize with cor vehicles ($Pcov_{\boldsymbol{\tau}}(\lambda)$) in the second, when we optimize for pedestrians ($Pcov_{\mathbb{1}}(\lambda)$).

Fig. 3 reports the metric in Eq. (8) and shows two very relevant conclusions. The first is that $Vcov_{\boldsymbol{\tau}}$ reaches 90% coverage with $\lambda = 15$, 95% coverage with $\lambda = 20$ and 99.9% coverage with $\lambda = 35$ while $Vcov_{\mathbb{1}}$ needs 33% and 25% more gNB to cover 90% and 95% of the vehicles, and can not reach 99.9% even with $\lambda = 85$. Considering that vehicles coverage for autonomous driving requires a high reliability, we see that there is a relevant difference when we specifically optimize for vehicles, rather than for pedestrians. The second conclusion is more generic: so far we did not have any concrete indication of how much we need to increase the density of gNBs to achieve vehicles coverage, and this result tells us that in urban areas, a reasonably low density can still be sufficient for reliable service.

Fig. 4 instead tells a different message. There is a remarkable difference in the coverage of pedestrians when optimizing for vehicles or not. In particular, the vehicles' optimization does not allow us to cover 95% of the ground. Note also that if we would consider non public areas, or areas non adjacent to streets (like parks) this metric would be even worse.

The takeaway for the operator that needs to start deploying gNBs for LoS communications is that the goals of covering vehicles or pedestrians are concurring ones. Optimizing for vehicles would reduce significantly the required density of gNBs but would not allow to reliably cover pedestrians positions.

VI. Conclusions

The foreseen densification of gNBs and the advancements in vehicular communications are playing a pivotal role in the deployment of XG access networks in ultradense urban areas. This paper proposes a novel data-driven method to optimize the placement of such gNBs and provide crucial insights to the network operators to understand how the two coverages, for vehicular communication and pedestrians, are intertwined. The results show that a reasonably low density of gNBs is sufficient to provide 95 % coverage in urban areas, but that at the same time optimizing the coverage only towards the roads with the most traffic will affect coverage for pedestrians.

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