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Strategic Deployment of RSUs in Urban Settings: Optimizing IEEE 802.11p Infrastructure

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Abstract

The efficient deployment of Roadside Units (RSUs) in an infrastructure based on IEEE 802.11p is essential for delivering Internet-based services to vehicles. In this paper, we introduce novel strategies that, in contrast to prior works, exclusively rely on the average vehicular density within specific urban areas, and these strategies depend on a performance model of IEEE 802.11p for guidance and decision-making regarding RSU placement. This minimal upfront information contributes to the practicality and ease of implementation of our strategies. We apply our strategies to three real-world urban scenarios, utilizing the ns-3 and SUMO simulators for validation. This study contributes to three fundamental aspects. First, we establish that any efficient deployment of RSUs is closely linked to the unique characteristics of the city under consideration such as the street layout and spatial density of vehicles. In other words, the characteristics of an efficient RSU deployement are unique to each city. Second, we show that the optimal strategy is not to place the RSUs at the locations with the highest traffic density. Instead, with the help of an analytical performance model of IEEE 802.11, we propose a more efficient strategy wherein the location of each RSU is determined to maximize the number of vehicles receiving the target QoS. This can lead to a significant drop in the number of RSUs required to equip a city. Finally, we demonstrate that, by preventing the use of the lowest transmission rate of IEEE 802.11p at each RSU, a collective benefit can be achieved, even though each RSU experiences a shorter radio range.

Keywords: IEEE 802.11p, SUMO, ns-3, vehicular networks.

1. Introduction

Electric, connected and ultimately autonomous vehicles are at the forefront of a shift in the automotive industry, ushering in an unprecedented era of innovation and revolutionizing the way we perceive and experience the future of transportation. This transformative wave not only redefines how vehicles propel themselves, but also how they interact with their environment and their passengers, heralding an exciting era of sustainable, intelligent and autonomous mobility solutions. The integration of vehicle connectivity is a critical element for many compelling reasons, primarily

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focused on enhancing safety and traffic management and improving the passenger experience through advanced navigation and a wide range of infotainment services. Consequently, deploying a robust network infrastructure becomes mandatory to enrich the overall passenger travel experience. This infrastructure should offer real-time information regarding traffic conditions and weather forecasts, as well as enable video streaming and conventional Internet applications.

The IEEE 802.11p standard, designed by the IEEE for vehicle network communication, is a logical and promising choice when considering communications technology. IEEE 802.11p operates within unlicensed frequency bands, setting it apart from alternatives such as cellular technologies, including 5G and 6G. This characteristic provides a significant advantage to stakeholders in multiple ways. From a cost-effectiveness perspective, the absence of licensing fees and the availability of unlicensed spectrum make 802.11p an economically viable choice. The utilization of unlicensed frequency bands enhances operational convenience, as it allows for flexible deployment without the constraints associated with licensed spectrum allocation, leading to more accessible and adaptable implementations in a variety of scenarios. Moreover, the IEEE 802.11p standard has demonstrated effectiveness in transmitting such critical communications [1, 2, 3] and has proven its effectiveness across a variety of environments [4, 5, 6], owing to its relative simplicity. This ensures its relevance and practicality in vehicular communication scenarios, positioning it as a robust and economically viable option for stakeholders

The described scenario envisions the installation of Roadside Units (RSUs) across urban areas to extend internet-based services like content streaming to moving vehicles, as depicted in Figure 1. For a Video-on-Demand (VoD) application, the process begins with video frames being transmitted from the hosting servers to the RSUs via high-speed wired connections. The RSUs then broadcast these frames to vehicles using IEEE 802.11p radio channels. Here, the network infrastructure primarily comprises strategically placed RSUs within the specified coverage area, all connected to a Wide Area Network (WAN) through wired links. Acting as gateways, these RSUs provide connectivity to nearby vehicles subscribed to the multiservice network platform. Although our work initially centers around video applications, it is not exclusive to them. This VoD application serves as a foundational test case for our scientific exploration, with the understanding that our methodology can be tailored for various internet-based solutions and future vehicular applications. This adaptability highlights the broad applicability and flexibility of our research, allowing for exploration and innovation beyond video applications, encompassing different fields and internet-based services.

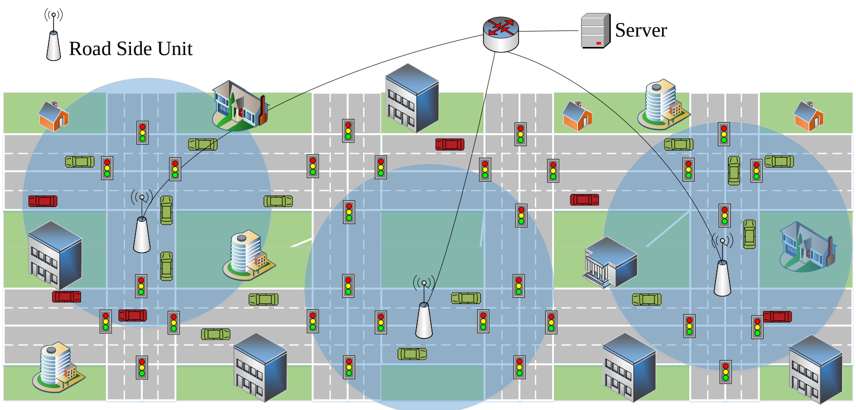


Figure 1: IEEE 802.11p-based architecture for providing connectivity to urban passing vehicles

However, and despite technological advances and the availability of recent technologies, fundamental questions about the optimal deployment of a high-performance multiservice network infrastructure capable of supporting vehicular applications still need to be answered, despite technological advances and the availability of recent technologies. One such question concerns the location and number of roadside units (RSUs), especially in densely populated urban areas like a city center. Do RSUs need to be deployed mainly in areas with higher vehicle density? Or rather at crossroads where the RSUs' cover range will be the largest? A follow-up question pertains to the "right" number of RSUs. An adequate answer to that question should avoid both the pitfall of an undersized and thus ineffective deployment, as well as the exceeding cost of an oversized deployment. Figure 1 illustrates a deployment with three RSUs following a regular pattern across an area of about 0.7 km^2.

Unfortunately, deciding the locations and the number of RSUs to be deployed for the sake of throughput-intensive services in an urban area is a complex matter. Firstly, vehicles are mobile and their trajectories are both uncertain and highly constrained by the actual plan of streets. Clearly, any adequate deployment for a given city will be of little value for another. Secondly, the performance of wireless communications are highly variable both in space and time because of the vehicles' mobility. Thirdly, many applications like VoD are known for their stringent QoS (Quality of Service) requirements in terms of throughput and packet losses (delays are typically much less of a concern because of the buffering mechanisms). For all these reasons, strategies consisting in deploying RSUs following a grid pattern, thereby not accounting for the actual vehicular traffic density, are likely to be inefficient.

In this paper, we study the opportunity for a stakeholder to deploy an 802.11p-based multi-services infrastructure intended to vehicles in dense urban areas. More precisely, our contributions are as follows:

- We propose several strategies to determine where and how many RSUs should be deployed based solely on the knowledge of the plan of streets and the spatial density of vehicles on these streets.
- We investigate the applicability of different definitions of density that take into account the particularities of cities, such as the number and length of lanes, junctions, etc.
- We apply these strategies on three scenarios (associated to the cities of Berlin, Manhattan, and Beijing) and compare their relative merits using realistic simulations combining ns-3 for the networking part, SUMO for the vehicles trajectories, and real traces for the videos.
- We provide guidelines for the deployment of RSUs that can be of interest for potential stakeholders contemplating the deployment of a multi-service infrastructure at the scale of a city.

The remainder of the paper is organized as follows. Section 2 discusses the related work. In Section 3, we explain the methodology to simulate realistic vehicular traffic and wireless communication with the use of two simulators. Section 4 is devoted to the description of the different strategies for the deployment of RSUs. We evaluate the strategies and discuss the corresponding results in Section 5. Section 6 concludes this paper.

2. Related work

Several papers have been published in the last few years on different aspects associated with vehicular network planning, specifically on the positioning of RSUs. In [7], the problem of having a maximum number of Dissemination Points (DPs) aiming at covering the largest number of vehicles served over a given area is considered. The authors carry out some initial simulations, from which they conclude that the best locations to place the DPs are the intersections between streets. Then, two different problems are considered. First, the main objective of their study is to maximize the number of vehicles that are contacted at least once by a DP. In the simulations, some traces of vehicles moving through cities are used. Based on these traces, the authors build an NxV matrix (intersections x vehicles) whose elements represent the intersections and have a value of 1 if the vehicle has passed through the intersection and 0 otherwise. The problem is then formulated as a Maximum Coverage Problem (MCP), which is NP-hard. The authors propose a greedy heuristic (MCP-g) which achieves a good approximation. Then, they resort to a subzone algorithm to divide the total area into subzones before solving the maximum coverage problem in each of them. In addition, the authors refine their approach to avoid the need to know the identity of each vehicle passing through an intersection: they only assume the knowledge of the total number of vehicles passing through the intersection. This leads to a 0-1 Knapsack Problem (KP) model, which can be solved in this case in polynomial time. Secondly, the authors consider the case in which vehicle-to-DP contact times have an impact on the dissemination process. In this case, their problem consists of positioning k DPs in order to serve as many vehicles as possible during a minimum time period. The performance evaluation of the submitted proposals, such as the coverage ratio in front of the number of DPs, is carried out on different road topologies, representing portions of real urban areas.

In [8], the authors present a strategy for the deployment of RSUs in Vehicular Ad hoc NETworks (VANETs), which they call Minimal Mobility Patterns Coverage (MPC). The strategy introduced is spatio-temporal, encompassing spatial attributes and temporal characteristics, with the goal of maximizing coverage while minimizing the deployment cost through a reduction in the number of RSUs used. To reach an optimal placement, MPC is based on vehicle trajectories. Thus, in a first step, the authors use Formal Concept Analysis (FCA) to depict the mobility patterns of moving vehicles from trace files. A formal concept can be viewed here as a set of trajectories that share a set of junctions (aka intersections). In this step, because extracting all formal concepts from a large context requires high computation time, a QualityCover algorithm is used to extract a minimal set of relevant formal concepts. In a second step, the Minimal Covering Junctions set is obtained, corresponding to the places where RSUs must be located to cover the extracted mobility patterns with a minimal number of RSUs. To evaluate the performance of their proposal, authors carry out different simulations by means of different well-established simulation tools (OMNeT++, MiXiM, SUMO and Veins), over two different scenarios. They evaluate different parameters related to the effectiveness (high coverage ratio with a minimum of RSUs) and efficiency (minimum latency and overhead) metrics and show the correct behavior of their proposal.

Another study has been published in [9], in which the authors propose an RSU deployment strategy based on traffic demand, which optimizes both the average data delivery delay in VANETs and the number of vehicles covered by RSUs. In the considered scenario, communications are carried out in multi-hop mode, using the vehicles themselves as potential relay nodes for the traffic of others. The deployment of RSUs is optimized to cover the cases in which there are not enough vehicles to act as forwarders. It is interesting to note that, under this working hypothesis, more (resp. less) RSUs should be deployed in areas where the vehicle density is low (resp. high).

In this paper, the assumptions made regarding vehicle traffic set it apart from previous work. The most restrictive assumption in our study is that we assume the average vehicle density over the area of interest is known. This contrasts with the work of [7, 8], where complete knowledge of individual vehicle trajectories was assumed. In our earlier research [10, 11], we examined the performance of an RSU-based infrastructure using knowledge of vehicle density and applying an analytical model for 802.11p, which was initially introduced in [12]. However, this current work delves into a more complex scenario, diverging from our prior studies. Unlike our previous work [10, 11], which focused on the more straightforward case of large highways with predictable vehicle trajectories, the present study explores the broader and more challenging context of urban environments. The current paper addresses the more complex case of urban environments where vehicle trajectories are much less predictable, and street patterns are typically irregular. Nonetheless, we show through simulations that, with the help of a predicting analytical model of 802.11p, efficient deployment strategies of RSUs can be performed. Note that a preliminary version of this paper was published in [13].

The notion of density is key to our study. In this sense, it is worth mentioning that the density metric can be considered in different ways with potential impact on the resulting RSUs deployments. For example, the density metric could be considered simply as the number of vehicles per square kilometer in the different areas of the city under study, but in this case, we would not be taking into account other relevant parameters, such as the area that is actually intended for circulation, nor the street topology. Thus, to present the results obtained with our proposal, we have considered different options, including the concept of density presented in [14]. In this latter work [14], the authors raise the need for a new metric to measure the density of vehicles in a vehicle network. They highlight the fact that, if only the number of vehicles per square kilometer is taken into account, the performance of the network (considering multi-hop vehicles communications) can differ greatly depending on the complexity of the city's road map. The following two parameters are defined and evaluated for multiple real cities: the Relationship between the number of streets and junctions in the city (SJR), and the Total Distance (TD) of a map as the sum of the length of all the lanes of each street per km^2:

$$SJR = \frac{\text{number of streets}}{\text{number of junctions}} \tag{1}$$

$$\text{TD(Map)} = \frac{\sum_{s \in S} \text{length(s)} \cdot \text{numLanes(s)}}{\text{area}} \tag{2}$$

where s iterates over each possible street, S denotes the set of all the streets of the map, *length(s)* returns the length (in km) of the street s, *numLanes(s)* returns the number of lanes in street s, and *area* denotes the area of the map in km^2.

It is interesting to note that the calculation of the number of streets can be ambiguous. For example, SUMO (Simulation of Urban MObility) [15] considers each edge between two junctions as a street, whereas with OpenStreetMap each street has a different "name" and therefore multiple edges can be part of the same street. In [14], in order to decide what should be considered as a street, the authors make use of an algorithm called RAV (Real Attenuation and Visibility) based on their previous research. They carry out simulations to study the dissemination of messages in 802.11p-based VANET networks, considering multi-hop communication between vehicles. Their simulation results indicate that cities with similar SJR values but different TD values obtain very different performances. Similar conclusions are obtained when comparing cities with similar values of TD but different values of SJR. This leads the authors to introduce a new density metric:

$$\text{Density} = \frac{\text{number of vehicles}}{\text{SJR} \cdot \text{TD}} \tag{3}$$

Then, the authors verify that cities with similar values of this new density metric obtain similar performance. Their tests, which are carried out in situations of low, medium, and high levels of load, validate the goodness of the proposed metric. It is worth noting that this new density metric's unit is [vehicles·km], and departs from that of the classic definition for density, namely [vehicles/km^2].

Table 1 summarizes our proposal's key contributions and differentiating features from previous studies encompass the following aspects: Firstly, our proposed strategies necessitate solely the knowledge of vehicle density within the areas of city planning for network infrastructure deployment. Our approaches, distinct from previous methodologies, require fewer input parameters (aka upfront information), significantly enhancing their practicality and ease of implementation. Secondly, to the best of our knowledge, we are the pioneering proponents of incorporating an analytical performance model of network communications into our strategy, thereby guiding and supporting RSUs deployment. As a consequence of these preceding innovations, our strategies exhibit scalability, effectively adapting to the scale of considered areas, such as the entirety of a large city's downtown and varying vehicular volumes. Lastly, we investigate the impact of considering different vehicular traffic densities that have been previously proposed on the best possible RSUs deployments found by our strategies.

3. Vehicular mobility and network simulations

In this work, we evaluate the performance of the proposed RSUs positioning strategies by using simulation environments, which we adapted to our needs. More specifically, we employed SUMO [15] and OpenStreetMap (OSM) [16] for the creation of urban environments, road networks and vehicle trajectory simulation. We use the ns-3 network simulator [17] for the assessment of wireless communications, consisting of the application of IEEE 802.11p access technology.

The characteristics of the different generated scenarios are detailed below.

3.1. SUMO simulator for vehicle trajectories

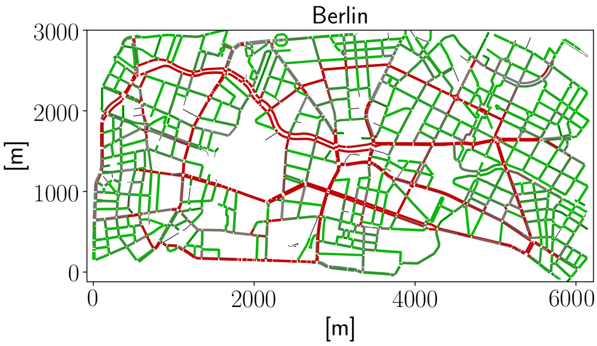
SUMO (Simulation of Urban MObility) is an open-source vehicular mobility simulator based on micro-simulations. It simulates vehicle behavior such as acceleration, braking, and lane change, among others. The selection of these models is determined by factors such as road type, the intended speed of each vehicle, and the prevailing traffic density. Any SUMO simulation comprises two main aspects: the road network and the traffic demand. On the one hand, the road network refers to edges, traffic lights, intersections, and other city elements. On the other hand, traffic demand refers to the number of vehicles circulating in the road network at a given time.

3.1.1. Road network

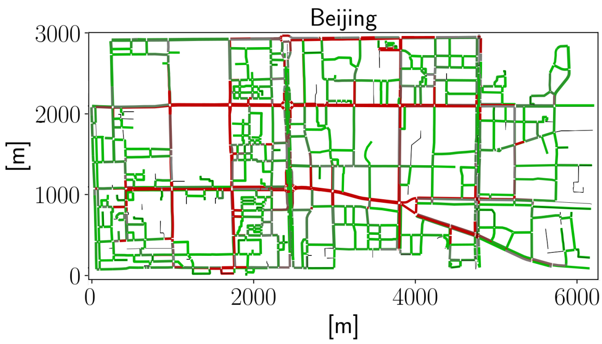
Three distinct city map excerpts were examined, namely Beijing, Berlin, and Manhattan (as depicted in Figure 2). These map excerpts were sourced from OSM repositories, a widely recognized and publicly accessible dataset that provides high-precision real-world cartographic data. It is worth noting that the transformation of the digital OSM map data into road network files, compatible with the SUMO simulation platform, was accomplished through the utilization of the *Netconvert* tool [18]. This conversion process was pivotal in ensuring that the maps could be seamlessly integrated within the simulation environment, thus facilitating a comprehensive evaluation of the RSUs placement strategies within these urban environments.

Table 1: Comparative Analysis of Related Work

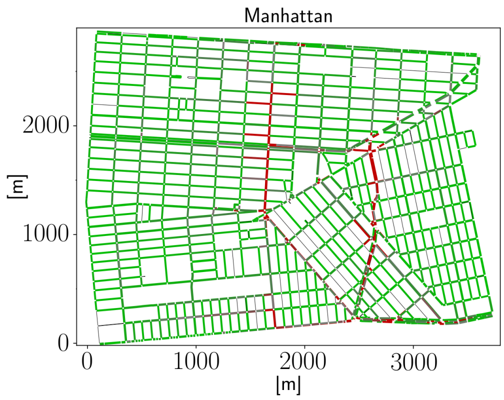
Reference	**Objective**	**Methodology**	**Key Differences with Proposed Research**
Trullols et al. (2010) [7]	Maximize the number of vehicles contacted by Dissemination Points (DPs)	Simulation-based approach using NxV matrix, greedy heuristic (MCP-g), and subzone algorithm	Focuses on intersections, assumes knowledge of individual vehicle trajectories, uses NP-hard problems and heuristics.
Yeferny et al. (2018) [8]	Maximize coverage while minimizing RSU deployment cost in VANETs	Spatio-temporal strategy using Formal Concept Analysis (FCA) and QualityCover algorithm	Utilizes vehicle trajectories and formal concepts, requires high computation time, different from our density-based approach.
Haiyang et al. (2021) [9]	Optimize RSU deployment based on traffic demand to minimize data delivery delay	Multi-hop communication mode, using vehicles as relay nodes, optimizing RSU deployment in low and high vehicle density areas	Relies on traffic demand and multi-hop communication, does not assume average vehicle density, different optimization criteria.
Sanguesa et al. (2016) [14]	Introduce new density metric to measure vehicle density in vehicular networks	Simulation of message dissemination in 802.11p-based VANET networks, uses SJR and TD metrics	Proposes new density metric, differs in considering street and junction relationships, different focus from our average vehicle density approach.
Begin et al. (2019) [10]	Examine performance of RSU-based infrastructure using vehicle density knowledge	Analytical model for 802.11p, simulations with realistic vehicle densities	Focuses on large highways with predictable trajectories, simpler scenarios compared to urban environments in current study.
Begin et al. (2020) [11]	Deliver VoD services using IEEE 802.11p to major non-urban roads	Stochastic performance analysis, simulations with realistic vehicle densities	Similar to [10], focuses on non-urban environments with predictable trajectories.
Amer et al. (2016) [12]	Optimize association in Wi-Fi networks for fairness	Analytical model for 802.11p, performance evaluation with different association policies	Provides foundational analytical model for 802.11p used in our study, different focus on Wi-Fi networks rather than vehicular environments.
Astudillo León et al. (2023) [13]	Propose strategies for RSU deployment in urban environments	Analytical performance model of IEEE 802.11p, strategies based on density matrix	Preliminary version of the current study, focusing on strategies and simulation results.
This Work	Efficient deployment of RSUs based on average vehicle density in urban areas	Analytical performance model of IEEE 802.11p, strategies based on density matrix	Assumes average vehicle density, fewer input parameters, focuses on urban characteristics and practical implementation, uses predictive model for RSU deployment.



(a) Berlin



(b) Beijing



(c) Manhattan

Figure 2: Three city maps are taken into consideration. The representation of vehicle density on the street segments is achieved through color-coding: Red is used to signify a high concentration of vehicles per unit of space, while Green is employed to indicate a lower density.

3.2. Traffic demand

To reflect that vehicle mobility is uncertain, highly constrained, and restricted to the city roadmap, we use different SUMO traffic generation tools to generate vehicle trajectories in realistic urban scenarios. In practice, we consider two types of traffic. On one side, vehicle trajectories intended to induce congestion on the map are characterized by background traffic. The background traffic rate is held constant during the entire simulation. On the other side, deterministic traffic, with predefined routes for specific vehicles, is generated from an origin to a destination. This deterministic traffic is used as probing traffic, allowing the capture of measurements on the respective vehicles as well as the validation of the forecasting model used in our deployment strategies in densely urbanized scenarios.

With the traffic generation tools provided by SUMO, a given route can be assigned to a single vehicle or to multiple vehicles (e.g., flows of vehicles). In this work, we use RandomTrips (RT) and other SUMO generation tools such as OD2Trips (OD2) and DUARouter (DUAR) to generate the routes. Background traffic is generated using the RT tool, where a set of random trips is created within a predefined time interval. Key parameters such as road network, simulation duration, vehicle attributes and arrival rates are taken into account in the process. In contrast, deterministic traffic is generated using the OD2 and DUARouter tools, driven by the use of origin-destination (O/D) matrices from OD2 that establish origin and destination points. These matrices form the basis for trip list generation, aligned with the predetermined numbers of vehicles stipulated within the O/D matrices. Besides, we use the DUARouter tool to import different demand definitions. In our case, we use as the input of DUARouter the list of trips generated with OD2. Finally, DUARouter generates a list of routes that includes the precise path between the origin and destination points.

3.3. Density metrics

As previously mentioned, the solutions presented in this paper are based on the knowledge of the density of vehicles in the different sub-zones of a city. The basic way to evaluate this density is simply to compute the ratio between the total number of vehicles in a given sub-zone and its area leading to the following definition:

$$\text{Classical density} = \frac{\text{number of vehicles}}{\text{area}} \tag{4}$$

However, as discussed in the related work section, some researchers have concluded that there are other relevant parameters to consider, such as the number of streets, lanes per street, or junctions (aka intersections). For the evaluation of our proposals, we investigate different definitions for the density metric to see if they may lead to different conclusions. Thus, in addition to the classic definition of density, we have used the definition proposed in [14] (see Eq. 3). In this definition, one of the parameters to be considered is the number of streets, which presents some ambiguity.

In the case of SUMO, each segment between two junctions is called an edge, and an edge can comprise one or several lanes, as shown in Figure 3. Besides, each lane has its own direction, e.g., east or westbound. By default, SUMO does not have a specific definition for a street.

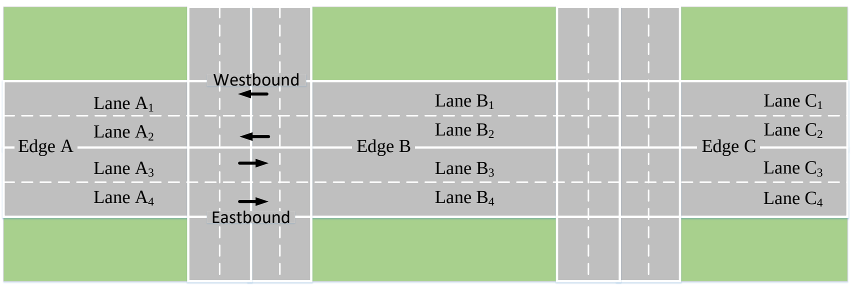
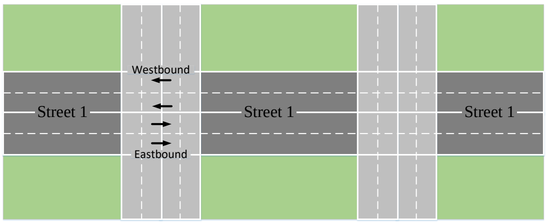
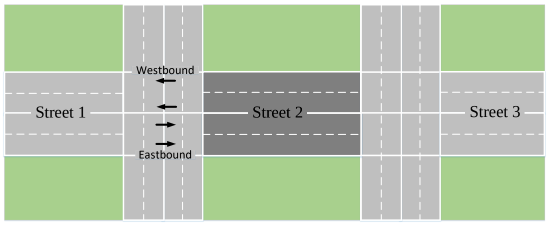


Figure 3: Representation of edges, lanes and directions in SUMO.

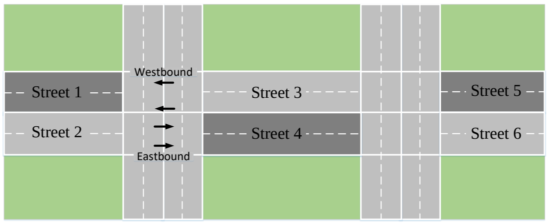
As we need to define what we consider as a street, we can consider different possibilities of grouping edges, lanes and directions in one street. We have considered three possibilities, represented in Figure 4: (a) Grouping edges, lanes and directions, (b) Grouping lanes and directions, and (c) Grouping only lanes. If applied to the example of Figure 4, the number of streets would be 1, 3 and 6 streets, respectively. Note that we are able to group edges belonging to a same street because of the codes that SUMO uses to uniquely identify each edge.



(a) Grouping edges, lanes, and directions



(b) Grouping lanes and directions



(c) Grouping lanes

Figure 4: Three options to count the number of streets. In addition to the classical density definition, each of these options will lead to a different definition of density.

Table 2 reports the numerical value of the SJR parameter for the three previous cases. Not surprisingly, the SJR value varies greatly depending of the street definition, ranging for instance from 0.76 in case of the first definition up to 2.33 in the case of the third definition. Note that the number of junctions in Table 2 simply relates to the number of junctions between the different edges.

Table 2: Computation of the SJR metric depending on the criteria used. This SJR metric is used by the three alternatives to classical density definitions.

City	**Junctions**	**Grouping edges, lanes and directions**		**Grouping lanes and directions**		**Grouping lanes**	
		Streets	**SJR**	**Streets**	**SJR**	**Streets**	**SJR**
Beijing	806	613	0.76	1375	1.71	1877	2.33
Berlin	1002	1389	1.39	2237	2.23	2474	2.47
Manhattan	851	791	0.93	1609	1.89	2039	2.40

To account for the size of the considered area, most previous works resort to its surface. However, in [14], the authors suggested that the Total Distance (TD) parameter may represent a better way to capture the size of a given area. TD is simply computed as the sum of the length of all the lanes of each street per km^2 (see Eq. (2)). Table 3 shows the corresponding values for our three considered city maps. In Table 4, we show the total number of vehicles needed in each city to obtain a density value equal to 400, considering the different density metrics presented. Note that these values were obtained using the SJR and TD metrics previously presented in Tables 2 and 3, respectively.

Table 3: Values for the TD metrics for the studied maps.

City	$\sum_{s \in S}$ **length(s)** $\cdot$ **numLanes(s)** (in km)	**Area** (in km^2)	**Total Distance** (TD) (in km^{-1})
Beijing	315.46	18.36	**17.18**
Berlin	360.89	19.53	**18.44**
Manhattan	231.84	10.73	**21.61**

Table 4: Number of vehicles required in the simulation to obtain a level of density of 400 for each the four different definitions.

City	Classical density	Grouping edges, lanes and directions	Grouping lanes and directions	Grouping lanes
Beijing	7344	5227	11725	16005
Berlin	7812	10246	16502	18250
Manhattan	4292	8033	16341	20708

3.4. ns-3 simulator for network communication

We conduct the network communication using the network simulator ns-3 version 3.29. We employ the IEEE 802.11p standard, and Table 5 provides the relevant information on radio ranges and transmission rates. We let 802.11p select the current transmission rate for a vehicle using the ideal Wi-Fi manager of ns-3. Note that the vehicles' location, mobility, and trajectories were directly derived from the outcome of the SUMO simulator. A comprehensive summary of the main parameters used by ns-3 to simulate the different network layers in our vehicular environment can be found in the Table 6. Within the upper layer, we have implemented a client/server video application, where the server transmits video content and the vehicles subsequently receive and reproduce it. We employed real video traces from the dataset provided in [19] to simulate and analyze the performance of various video applications, allowing researchers to gain valuable insights into the behavior of these applications under real-world conditions. We chose a video application for this research, but it could be any Internet-based application. Note that in our simulation environment, we did not configure a routing protocol since we are working in V2I (Vehicle-to-Infrastructure) mode. In this mode, vehicles communicate only with the infrastructure (namely, through RSUs) and not with each other. As for the radio propagation loss model, we followed the guidelines for urban scenarios provided in [20]. Specifically, we used the Friis model, aligning the parameter values with the recommendations from the same source [20].

Table 5: Description of the 6 communication zones of IEEE 802.11p occuring with the combination of the Ideal WiFi manager of ns-3 and the Friis propagation model.

Zone number	**Radio range (meters)**	**Transmission rate, T_j (Mbps)**	**Achievable throughput, A_j (Mbps)**
H1	60	27	12.69
H2	80	18	9.9
H3	92	12	7.5
H4	110	9	6.02
H5	126	6	4.34
H6	144	3	2.35

Table 6: Description of the networking layers used by ns-3.29.

ns-3 IP stack	Parameter	Value
Application	Traffic type	Video streaming (Star Wars)
	Packet size	Variable
	Data rate	Maximum (regulated by TCP)
	Codec	H265/HEVC 8.0
Transport	TCP congestion control	New Reno
Routing	Routing protocol	None (Vehicle-to-insfrastructure mode)
MAC	MAC Helper	NqosWaveMacHelper
	Wi-Fi Manager	ns-3 Ideal Wi-Fi manager
Physical	Phy standard	802.11p
	Propagation Loss Model	Friis

In our work, as soon as a vehicle enters the coverage area of an RSU, traffic downloading is initiated (as fast as possible), and this process is maintained until the vehicle leaves the RSU coverage area.

4. Proposed Strategies

Three distinct strategies are proposed and investigated to facilitate and guide the placement of RSUs within an urban area. They are all model-driven taking advantage of the forecasts of a performance model. The associated model is described in the following section.

4.1. Forecasting the performance of 802.11p

To be efficient, any RSU deployment strategy must account for the average level of vehicle density across the city, or better yet, reckon the throughput attained by each connected vehicle in return of a given RSU deployment.

In Appendix A, we discuss some of the existing analytical models to evaluate the performance of 802.11 communications. For our study, we rely on the analytical model, initially presented in [12] to determine the throughput achieved by each connected vehicle within a specific area and roadside unit (RSU) locations. The model accounts for the different transmission rate zones or physical rates around an RSU, as detailed in Table 5, where negotiation between the RSU and vehicles occurs.

The analytical model works as follows. With 802.11p, the radio range of any RSU is divided into Z separate zones, each of them corresponding to a different value of transmission rate (aka physical rate) negotiated between a vehicle located in that zone and the RSU. Note that these transmission rates correspond to different MCS (Modulation and Coding Schemes) whose choice is mostly driven by the quality of the radio channel. Of course, the precise length of these zones strongly depends on the propagation environment. In 802.11p, there is a total of Z=6 zones as shown by Figure 5. Due to the overhead of the IEEE 802.11p protocol (backoff, Ack, DIFS, SIFS,. . .), the RSU will on average transmit its data at a rate referred to as the attainable throughput and which is by definition lower than the transmission rate. Note that the attainable throughout is computed assuming that the RSU has a single vehicle to serve. However, because multiple vehicles may compete to obtain their data from an RSU, the throughput attained by each of them is (again) lowered (by a factor generally different from an inverse proportion of the number of vehicles [21]) and denoted in this paper as its attained throughput.

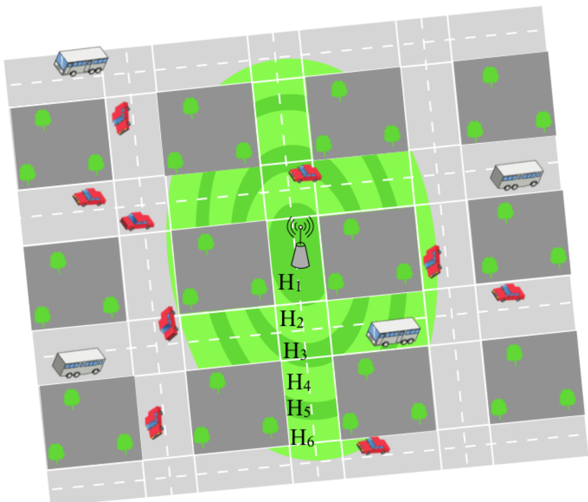


Figure 5: An RSU with its 6 zones corresponding at different transmission rates (MCS).

In this paper, we use the following notation. Given a vehicle in the j-th zone, we let T_j, and A_j denote its transmission rate and achievable throughput, respectively. Clearly, we have $A_j \leq T_j$. Table 5 reports the corresponding values of T_j and A_j when using the Ideal Wi-Fi manager of ns-3 for packets of size 1500 bytes and the Friis free space propagation model. Note that in practice the specific values for A_j will be updated based on the RSUs' specifics (e.g., antenna, transmission power) and on the propagation model for the considered scenario (e.g., path loss exponent).

Denoting by n_j the number of connected vehicles in the j-th zone of an RSU, and assuming that n_j follow a Poisson distribution, we can then compute the attained throughput of a given connected vehicle i as [11]:

$$B_i = \frac{1}{\sum_{j=1}^{Z} \frac{n_j}{A_j}} \tag{5}$$

Note that the previous equation returns identical results for all vehicles associated with the same RSU, which is in line with the property of DCF known as the performance anomaly [21].

The model's effectiveness has been demonstrated provided the exchanged traffic is mostly downstream and that the number of vehicles in each transmission rate zone is not too far from Poisson. Its performance estimates closely align with those obtained through simulations using ns-3 and SUMO, differing by only 24%, despite its apparent simplicity. It is worth noting that this analytical model serves as the foundational element of the proposed deployment strategies. For a more in-depth review of this model, readers are encouraged to consult Appendix A or refer to [11], where we applied the same model in a more straightforward scenario, specifically a major highway.

4.2. Key Parameters

Before presenting the different strategies, we introduce the following key parameters and the corresponding notations.

Density matrix, D. This matrix depicts the average vehicular density within each part of the area of interest. The creation of a realistic matrix denoted as D for the city maps under consideration is executed through the utilization of the SUMO simulation framework. In this sense, the urban map undergoes partitioning into uniform squares, each with a predefined dimension, for instance, 10x10 meters, and within these demarcated squares, the mean vehicular count is recorded. The corresponding measurements are organized into a matrix called as the density matrix, which is denoted by $D = (d_{i,j})$.

Penetration rate, p. To account for the fact that the Internet service provided by the RSUs may not be subscribed to by all vehicles, a parameter called the penetration rate, represented by p $(0 < p \leq 1)$, is introduced. This parameter simply means the ratio of vehicles that are expected to be subscribed to the Internet service. Note that the spatial distribution of vehicles that the RSUs will need to serve is simply given by the matrix $p * D$.

Target QoS, q. A vehicle's quality of service (QoS) will be considered satisfied when it is able to achieve a minimum download rate of q Mbps. Vehicles that achieve download rates greater than q Mbps are referred to as served vehicles in this section.

Covering rate, α. A successful RSU deployment is determined when the *alpha* threshold $(0 < \alpha \leq 1)$ is exceeded, indicating that the proportion of connected served vehicles (i.e., capable of downloading data at a rate greater than q Mbps) has been reached.

4.3. Definition of the Strategies

The primary objective of each strategy under consideration is to determine the minimum number of RSUs required and their spatial allocation, thereby enabling the achievement of download rates exceeding q Mbps for a specified proportion α $(0 < \alpha \leq 1)$ of the connected vehicles. We assume that the density matrix for the area of interest, D, as well as the values of the parameters p, q and α are known from the strategies. The foundation of these strategies lies in the utilization of a greedy algorithm. At each iteration, a new RSU is positioned at a location selected to maximize a predefined criterion. Each strategy is distinguished from the others by the unique formulation of its criterion. The deployment of RSUs is initiated from an initial void state, and the termination condition is met as soon as a proportion α of the connected vehicles can reliably attain the minimum download rate of q Mbps.

The steps taken by each strategy in each iteration are described by Algorithm 1. The core of the algorithm is the execution of the following three fundamental functions:

- The set of indices of the D matrix that are within an RSU's radio range located at (i, j) is returned by the function $range(i, j)$.

- The fraction of vehicles within a RSU's radio range located at coordinates (i, j) with a received throughput of at least q Mbps is determined by the function $served(D, (i, j), q)$. This computation is based on the performance model initially introduced in [12]. We detail the $served(.)$ function in Appendix B.
- A proportion c of vehicles within an RSU's radio range placed at coordinates (i, j) is removed by the function $update(D, (i, j), c)$.

Algorithm 1: Baseline of strategies

Inputs : Density matrix, D; Penetration rate, p; Target QoS, q; Covering rate, α.
Result: A set of RSUs with their location.

```
1  X=0 //The current proportion of served vehicles.
2  D = p * D
3  Total_Density= Σ_(i,j) D_i,j
4  while X < α do
5      (i, j) = argMax_(i,j) f(D, (i, j)) //Compute the best location for the new RSU
6      c = served(D, (i, j), q) //Compute the proportion of vehicles in range(i,j) that can be served (with Eq. 5)
7      veh_cov = c · Σ_(k,l)∈range(i,j) d_k,l //Compute the number of vehicle served
8      X = X + veh_cov / Total_Density
9      D = update(D, (i, j), c) //Remove the vehicles that are served by the new RSU from the matrix D
10 end
```

For an efficient RSU deployment strategy, the general framework is formulated by Algorithm 1, and can be expressed in several ways by contemplating various interpretations for the $f(.)$ function (as described in line 5 of Algorithm 1).

The three following potential alternatives for the function $f(.)$ are taken into account.

- Strategy **Max density**: A new RSU is placed where the density reaches its maximum. Consequently, $f(D, (i, j)) = d_{i,j}$.
- Strategy **Max density radio range**: A new RSU is placed where the number of vehicles within its range is maximized, independent of their performance. Consequently, $f(D, (i, j)) = \sum_{(k,l)\in range(i,j)} d_{k,l}$.
- Strategy **Max vehicles served**: A new RSU is placed where the maximum number of vehicles is served, ensuring they download at a minimum rate of q Mbps. Consequently, $f(D, (i, j)) = served(D, (i, j), q) \cdot \sum_{(k,l)\in range(i,j)} d_{k,l}$.

Lastly, it is worth noting that, because of our throughput computation (see Section 4.1), the p and q parameters influence the proposed deployment strategies only through their product $p.q$. This means that for a given scenario, considering (p, q) = (0.3, 3Mbps) is identical to considering (0.1, 9Mbps).

4.4. A Simple Example

We use the simple example of Figure 6 to describe how each strategy will proceed with its first step on it. This example should be seen as a toy example. The density matrix (of size 5×7 here) represents a tiny excerpt of a city, which comprises a single segment of a street. We assume that the density values of Figure 6 already account for the penetration rate (which is the same as assuming a value of p equal to 1). Note that squares void of street have a density of 0.0. To keep this example simple and tractable by hand, the radio range of each RSU covers the square hosting the RSU along with the 8 adjacent squares.

For the **Max density** strategy, the first RSU is added at location $(4, 3)$ since this square has the maximum density (i.e., 3.0).

For the **Max density radio range** strategy, the first RSU is added at location $(3, 4)$. With this location, the density of the 9 squares around it is maximized (i.e., 14.5).

For the **Max vehicles served** strategy, the RSU is added at the location where the number of vehicles downloading at least at q Mbps is maximized. Due to the CSMA/CA mechanism of 802.11p, we need to account for the mean number of vehicles in each of the 6 communication zones of the RSU before estimating the download rate of any vehicle within this RSU radio range. This is precisely what the performance modeling of 802.11p introduced in Section 4.1 and detailed in Appendix A (see Eq. 5) does. Assume that the central square of the radio range (where the RSU is located) is served with an achievable throughput of $A_1 = 12.69$ Mbps and that the 8 other squares are served with an achievable throughput of $A_6 = 2.35$ Mbps. Equation 5 indicates that the attained throughput for a vehicle connected to a new RSU at (line, column) = (3,2) is 0.21 Mbps ($= 1/(\frac{1.5}{12.69} + \frac{11}{2.35})$). If the target QoS q is set to $1Mbps$, then this RSU alone does not accommodate the needs of all vehicles within its communication range. Hence, we rely on the $served(.)$ function to compute the proportion c of vehicles for which the QoS requirements are verified. In our example, we look for c such that $1/(\frac{c \cdot 1.5}{12.69} + \frac{c \cdot 11}{2.35}) = 1.0$ Mbps and we obtain $c = 0.21$. In other words, 21% of vehicles located within the radio range of this RSU are downloading at a sufficient rate (> q Mbps). Given the density matrix, this proportion translates to $0.21 \cdot (11 + 1.5) = 2.625$ vehicles. The **Max vehicles served** strategy evaluates this number of vehicles for all squares of the density matrix and retains the one resulting in its maximal value for the RSU location. In our example, this happens to be at location $(2, 2)$ where a proportion of 0.44 of the vehicles in the radio range are served for a total of 3.08 vehicles.

After having chosen the location of its next RSU, every strategy proceeds with the update of the density matrix D as follows. It computes the proportion of vehicles c receiving a sufficient level of QoS (following the same principle as for the **Max vehicles served** strategy) and subtracts this proportion from the matrix D for the squares in the radio range of the new RSU. Lastly, the strategy updates the global percentage proportion of served vehicles. For instance, in the case of the **Max vehicles served** strategy and denoting by X the current percentage proportion of served vehicles, it is simply performed through: $X = X + \frac{3.08}{Total\_Density}$. Each strategy keeps repeating these steps until X reaches α.

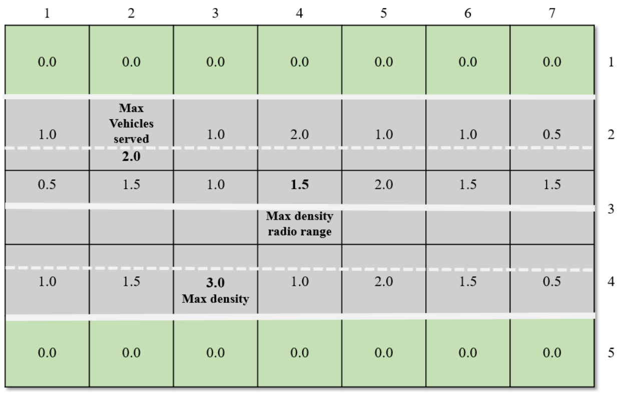


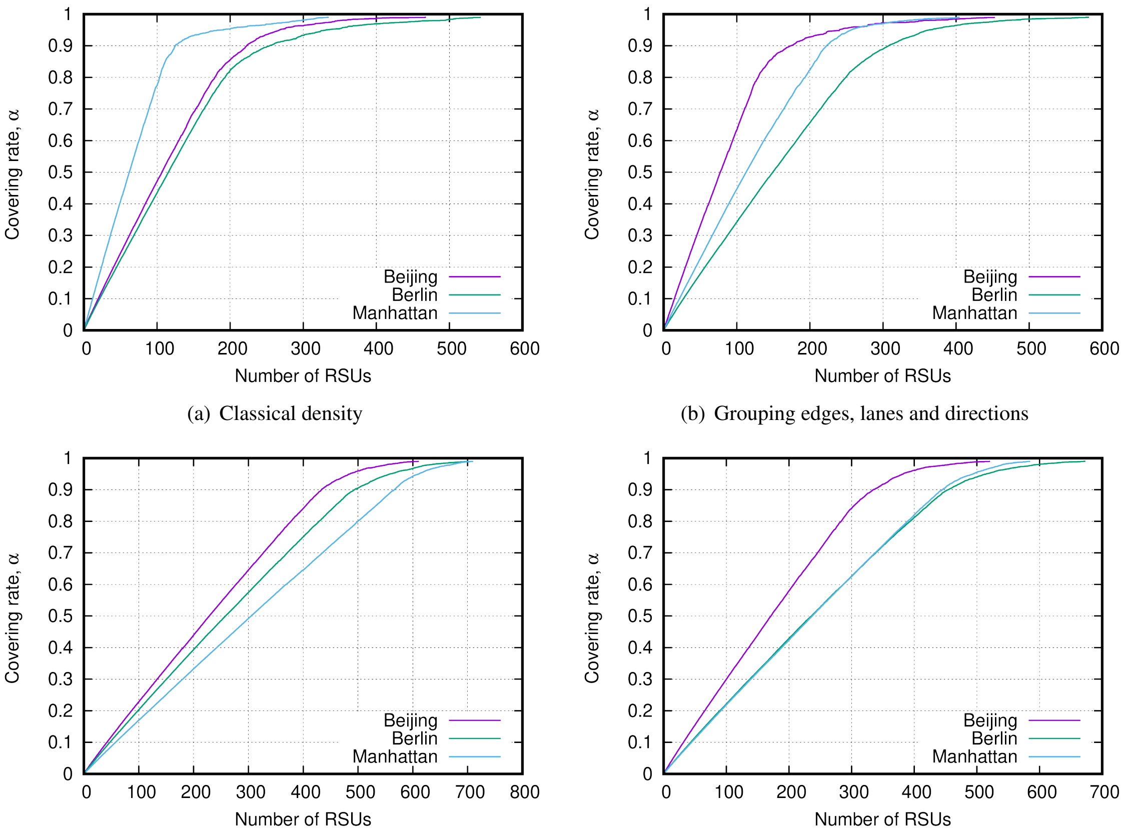
Figure 6: A simple example of street along with its density matrix to showcase each considered strategy for the deployment of RSUs. The numerical value in each square denotes the corresponding vehicle density. The grayed area represents a 2x2-lanes street while the white area indicates the area not accessible to vehicles.

5. Numerical Results

Before diving into the numerical results, we want to underline that the efficiency of an RSUs deployment strategy can be directly appraised by the resulting level of connectivity between vehicles and RSUs. Hence, most of the following figures pertain to the covering rate α as a measure of the attained connectivity.

Recall that for the sake of our RSU deployment strategies, the parameters p (penetration rate) and q (target QoS) only matter through their product $p.q$.

Therefore, we limit our analysis to the influence of the penetration rate p on RSU deployments without delving into the different values of the QoS parameter q. This section keeps this q parameter fixed at 1 Mbps.



(a) Classical density

(b) Grouping edges, lanes and directions

(c) Grouping lanes

(d) Grouping lanes and directions

Figure 7: Number of RSUs as a function of the coverage parameter α for each of the four density definitions. Strategy: **Max vehicles served**. Density=300 (vehicles per km^2 for case (a) and vehicles·km for the rest of the cases.) Target QoS, q=1Mbps. Penetration rate, p=30%.

5.1. Influence of the vehicle density definition on the RSUs deployment

In this Section, we aim to determine if there is a strong correlation between one of the density metrics (as discussed in Section 3.3) and the number of RSUs to deploy. For instance, it would be the case if a given density value (for a given density metric) led to the same number of RSUs whatever the city. In Figure 7, we represent the covering rate α (recall that this refers to the proportion of vehicles served) as a function of the number of deployed RSUs under the **Max vehicles served** strategy for the three considered cities. While the four subplots correspond to a traffic of vehicles that was set to reach a density of 300, each of them relates to a different definition of the density. From Figure 7, we can conclude that none of the considered definitions of density conduct the number of RSUs to be deployed for the different cities to similar values. Indeed, the deployment is tightly linked to more complex phenomena such as the city map, the spatial distribution of the vehicles in the city, etc. Although not presented in this paper, we had similar outcome with the other strategies, and with other levels of density, target QoS q, and penetration rate p. Therefore, because the more complex definitions of density do not provide better results for our purposes than the simpler classical definition, for the remaining results, we consider only the classical definition of density to set the level of vehicular traffic.

5.2. Comparing the strategies

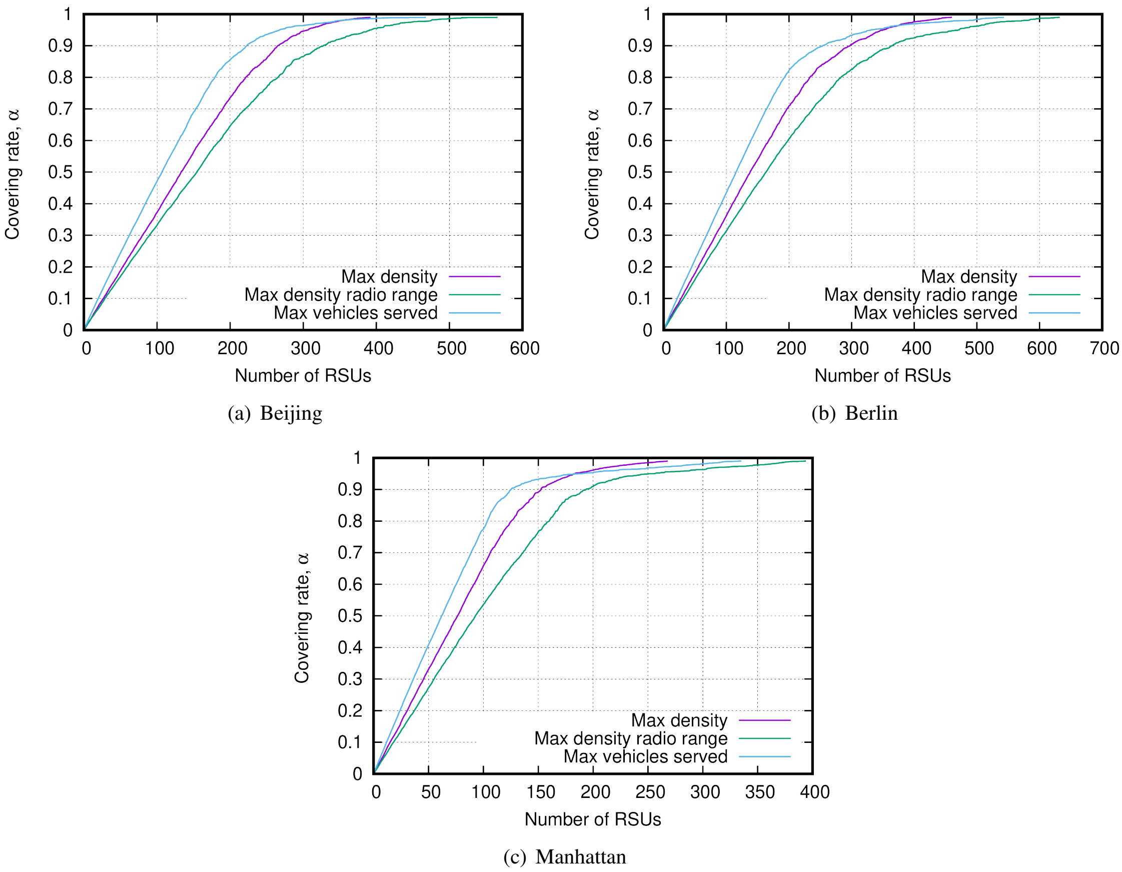


Figure 8: Number of RSUs as a function of the covering rate α for the three cities and for the different strategies. Density=300 vehicles per km^2. Target QoS, q=1Mbps. Penetration rate p=30%.

In Figure 8, a comparison of the discussed strategies described earlier in Section 4.3 is shown, considering a vehicle density of 300 vehicles per km^2, a desired QoS of q = 1Mbps, and a penetration rate of p = 30%. It appears evident that the **Max vehicles served** strategy exhibits superior performance when compared to the other strategies, necessitating fewer RSUs than the alternatives, regardless of the coverage rate α. This can be attributed to the fact that the **Max vehicles served** strategy focuses directly on the parameter we intend to optimize, which is α (i.e., the proportion of vehicles served). With the strategy **Maximum vehicles served**, a 90% α value can be achieved in the city of Beijing, using 223 RSUs, whereas the **Maximum radio range density** and **Maximum density** strategies require 328 and 266 RSUs, respectively.

In Figure 9, the positions of the RSUs chosen using the **Maximum vehicles served** strategy are shown for the cities of Berlin, Beijing, and Manhattan, together with their corresponding radio ranges. The RSUs are mainly located in the vicinity of streets experiencing heavy traffic. In the figures, streets with low vehicle density are depicted in green, while streets with high vehicle density are shown in red. The RSUs are represented by blue disks, indicating their radio coverage areas. It is evident that in areas with a higher concentration of vehicles, there are more RSUs strategically placed to ensure the target QoS. This distribution helps manage high demand and maintain continuous connectivity for vehicles. The visual representation highlights the effectiveness of our deployment strategy, ensuring that vehicles receive consistent and reliable service.

It is also shown in Figure 8 that the marginal gain over the coverage rate α decreases rapidly as the number of RSUs increases. For the **Maximum vehicles served** strategy for the city of Berlin, an increase in α from 0% to 43% is achieved with the initial 100 RSUs, whereas to increase α from 70% to 91% requires the same quantity of additional RSUs. Indeed, if α were to increase above 90%, deploying numerous additional RSUs would be necessary. Furthermore, the figure shows that, at excessively high levels of α, convergence of all strategies is observed. It should be noted that similar observations were made for other density levels and target QoS q, although they have not been presented here for the sake of conciseness. The **Maximum vehicles served** strategy is the one that has proven to be the most efficient in all scenarios considered and will be the one we will focus on in the rest of the paper.

5.3. Influence of the penetration rate on the RSUs deployment

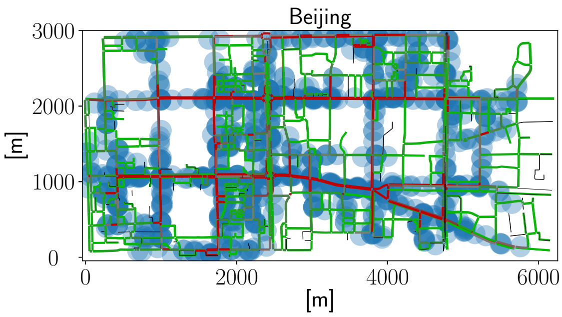
The evolution of the coverage rate α for the city of Beijing in terms of the number of RSUs is plotted in Figure 10, considering different penetration rate levels p, i.e., 10, 20, and 30%. Generally, various penetration rates result in significantly distinct deployment configurations. Certainly, when dealing with a greater number of vehicles to be served, it can be anticipated that a larger quantity of RSUs will be necessary. However, it should be noted that with a value of $\alpha = 0.9$, the same number of RSUs, specifically 176, is needed for both a penetration rate p of 10% and 20%. But with a 30% increase in the penetration rate, the number of RSUs experiences a notable increase, reaching 223. In summary, Figure 10 empirically demonstrates that, in addition to city structure and density, the penetration rate p should be considered as a significant contributing factor.

5.4. Evaluating the number of RSUs per kilometer

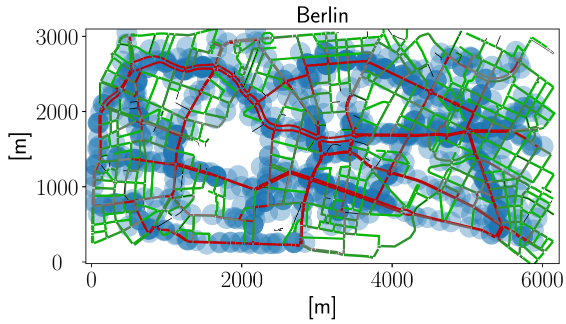
Table 7: Mean number of RSUs per kilometer to reach a covering rate, α of 0.7 and 0.9. Strategy: **Max vehicles served**. Density=300 vehicles per km^2. Target QoS, q=1Mbps. Penetration rate, p=30%.

	Beijing	Berlin	Manhattan
Covering rate, α = 0.7	0.485	0.457	0.384
Covering rate, α = 0.9	0.707	0.704	0.543

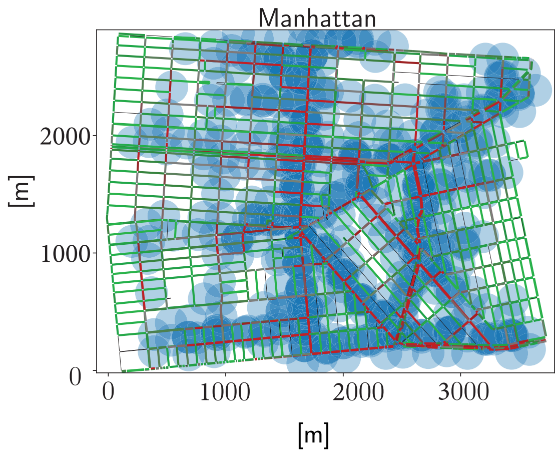
In Table 7, the number of RSUs per kilometer required to attain coverage rates of $\alpha = 0.7$ and $\alpha = 0.9$ with a target QoS q of 1 Mbps is reported for each city within the study. We calculated these results by obtaining the ratio of the total number of RSUs deployed within the specified city section to the cumulative lane length (as detailed in the second column of Table 3). It is observed that while Beijing and Berlin produce similar results, Manhattan necessitates a notably lower quantity of RSUs per kilometer. It can be attributed to the fact that Manhattan, as indicated in Table 4, has a lower number of vehicles compared to Berlin and Beijing to achieve an equivalent level of density. In summary, it can be deduced from the Table 7 that the deployment of RSUs, including their quantity and location, is highly dependent on the interaction between the city's layout and its traffic distribution. This dynamic nature precludes the application of a universal one-size-fits-all rule.



(a) Beijing.



(b) Berlin.



(c) Manhattan.

Figure 9: RSUs location. Blue disks represent RSUs and their radio range. Regarding vehicle density, red color represents a high concentration of vehicles, while green color is employed to indicate a lower density. Strategy: **Max vehicles served.** Density=300 vehicles per km^2. Penetration rate, p=30%. Target QoS, q=3Mbps. Covering rate, α=0.99.

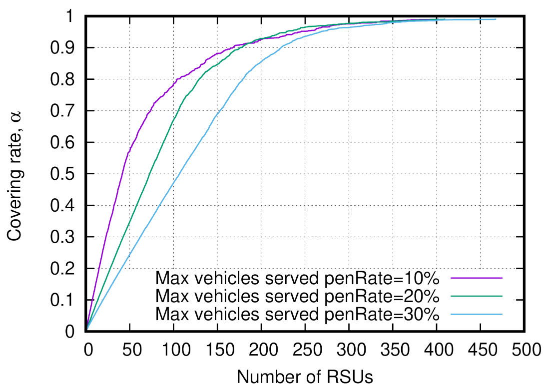


Figure 10: Number of RSUs as function of the covering rate (α) for the city of Beijing and for different penetration rate, p. Strategy: **Max vehicles served**. Density=300 vehicles per km^2. Target QoS, q=1Mbps.

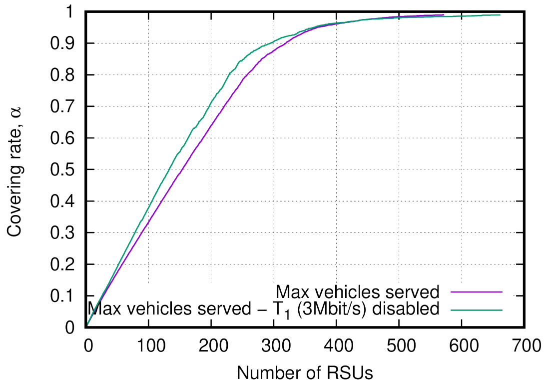


Figure 11: Number of RSUs as function of the covering rate, α, for the city of Berlin with the lowest transmission rate T_1 enabled or disabled. Strategy: **Max vehicles served**. Density=400 vehicles per km^2. Penetration rate, p=30%. Target QoS, q=1Mbps.

5.5. Precluding the use of the lowest MCS

In Figure 11, we show the covering rate α as a function of the number of RSUs in the case of Berlin. We consider two alternatives for the configurations of the RSUs: (i) a classical configuration wherein all MCS (Modulation and Coding Scheme) corresponding to the transmission rates of Table 5 made available by the IEEE 802.11p standard are enabled, and (ii) another configuration where the lowest MCS (denoted by T_1 and corresponding to a transmission rate of 3Mbps) is disabled. Under the latter configuration, a vehicle needs to enter into the second zone, i.e., H_2, of an RSU to begin to communicate with this RSU. Disabling the lowest MCS may help mitigate the so-called *Wi-Fi anomaly* where vehicles with high MCS (i.e., transmission rate) actually experience the same throughput as the vehicles with lower MCS [21]. This potential gain is clearly captured by Figure 11 that shows that, for a same level of target QoS q and of penetration rate, p, disabling the lowest MCS results into a deployment with less RSUs. For instance, the second configuration can save the deployment of 25 RSUs if the covering rate is set to $\alpha = 0.9$. Our proposed framework can help identify and evaluated such potential optimization resulting into substantial saving in terms of infrastructure cost.

5.6. Practical issues of deploying RSUs

These different examples show the efficiency of the proposed strategies in determining the number and locations of RSUs to provide network connectivity to vehicles taking only the urban density matrix as upfront information. Despite their relative easiness and practicality, these strategies should be accompanied by another study on the economic and logistical aspects implied by the deployment of such infrastructure if they were to be used by network operators or urban planners. It is worth noting, though, that IEEE 802.11p is by design compatible with IP networks and that, unlike cellular networks (e.g., 5G), it was designed to operate on unlicensed frequencies. This latter property can contribute to lowering the financial cost of 802.11p-based infrastructure solutions.

6. Conclusions

In this work, we propose and discuss several strategies for the efficient deployment of RSUs in an urban environment, with the main objective of providing Internet services through an 802.11p-based infrastructure. In contrast to most existing work, we rely on the density matrix, representing the average vehicle density within the examined area, as the sole pre-information for the strategies. Another peculiarity of our strategies is that they include a performance model to predict the IEEE 802.11p performance model intended to assist and guide the RSU deployment decisions. As a result, having only the average density of vehicles in the city streets as upfront information eases the application of our strategies, and accelerates the the execution of these strategies, without the need to run time-consuming discrete simulations. Strategies' upfront information are limited to (i) a density matrix reflecting the average number of vehicles in every part of the city; (ii) a target QoS parameter expressed as a desirable throughput rate for each connected vehicle; (iii) a penetration rate denoting the proportion of vehicles having subscribed to the Internet service; and (iv) a coverage rate expressing the probability that at any time a subscribed vehicles is experiencing a throughput rate higher than the target QoS parameter. We used two simulators: SUMO to determine realistic vehicular trajectories and ns-3 to evaluate the communication exchange between the connected vehicles and the RSUs. We considered three scenarios, each pertaining to the downtown of a real-life major city.

The following findings have been obtained in our study: First, we show that an efficient deployment of RSUs is closely linked to the unique characteristics of the city under consideration, specifically the street layout and vehicle spatial density. In fact, even by examining the particular characteristics of the city, it is not possible to predict the exact number of RSUs needed to achieve a predefined level of coverage. Second, our simulation results show that the optimal strategy is not to place the RSUs at the locations with the highest traffic density. Alternatively, placing the RSUs where the target QoS can be provided to the maximum number of vehicles is the most effective approach. In this context, we applied an analytical model to determine these locations. This observation challenges the conventional belief that RSUs should be strategically placed at street junctions. Finally, we show that precluding the use of the lowest transmission rate of 802.11p, i.e., 3 Mbps, at each RSU can actually result in a collective gain. Under such a configuration, RSUs spend most of their time serving vehicles at a greater pace while the downfall regarding the shorter radio range remains rather moderate.

In this work, we took the density of vehicles in the city for granted and we built strategies that leverage this information to deploy their communication resources. In our future work, we expect to investigate if the actual itineraries of vehicles and so the density of vehicles in the city can be changed to increase the QoS experienced by vehicles during their journey (without touching the underlying communication infrastructure). In practice, we will consider multiple itineraries for a vehicle entering the city, each path leading to a different duration but also QoS. We believe that such a feature could be of interest to commercial navigation systems such as Waze and Google Maps.

Acknowledgments

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Appendix A. Performance Modeling of 802.11p Communication

State of the Art

Modeling and forecasting the performance of network communications for IEEE 802.11p vehicular networks is well known to be a hard problem due to the vehicle mobility, the instability of the radio channel, along with the peculiarities of DCF (Distributed Coordination Function) at sharing the radio channel among the connected vehicles. The seminal performance model for 802.11 [22] has been extended to address the case of unsaturated networks (e.g., [22, 23]), error-prone radio channels (e.g., [24, 25, 26]), the IEEE 802.11p amendment (e.g., [27, 28]) or when multiple APs operating on the same radio channel overlap (e.g., [29, 30, 31]). In our case, we repurpose an analytical model, originally published in [12], to forecast the performance attained by vehicles along their journey in an urban area. Although this model can be viewed as a coarse-grained representation of the ground truth, its accuracy remains sufficiently good to be embedded within and assist some RSU deployment strategies.

Accuracy of the selected model

To validate the forecasting model synthesized by Eq. 5 in Section 4.1, we conduct experiments using the simulators SUMO (for the car trajectories and car traffic) and ns-3 (for the network communication and the transfer of video frames [19]). We consider an excerpt of Manhattan streets for which eight RSUs are deployed. Then, we introduce car traffic out of which 10% are assumed to be connected (i.e., using the VoD system provided by the operator) and we monitor the mean value of the attained throughout for 20 randomly selected vehicles. On the other hand, assuming the knowledge of the density matrix (providing us the mean number of vehicles per zone for each RSU) and the trajectories of the 20 monitored vehicles (i.e., times spent in each zone of each RSU), we are also able to compute the mean attained throughout for each of the same 20 vehicles. Figure A.12 summarizes the performance comparison in the attained throughput as delivered by the simulation against those returned by the analytical model. We observe that the model is generally accurate in its prediction with a mean relative error of 24%. The difference stems from the fact that the analytical model, unlike ns-3, does not take into account the effective trajectories of the vehicles, the effect of mobility on the transmission, the protocol stack, nor the physical layer. For further validation of the model, the interested reader can refer to [12, 11].

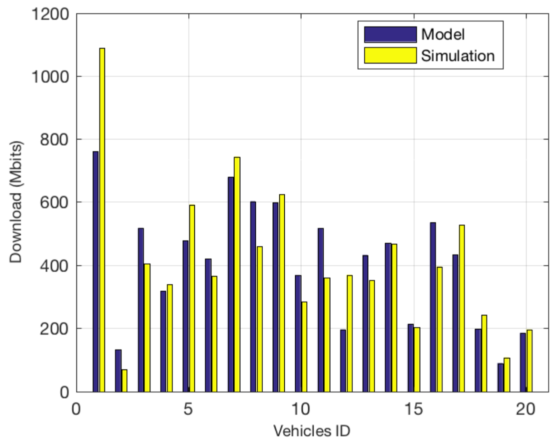

Figure A.12: Accuracy of the model at predicting the amount of downloaded data versus simulation with ns-3 and SUMO.

Therefore, using the formula of Eq. 5 and assuming that the density matrix of vehicles in the area of interest is known, we are able to approximate how much data and when a vehicle will receive from its RSU.

Appendix B. Description of the *served*(.) function

The $served(D, (i, j), q)$ function takes the following arguments:

- A density matrix $D = (d_{i,j})$ whose element $d_{i,j}$ indicates the number of vehicles to be served for the square located at the coordinates (i, j);
- (i, j), which denotes the coordinates of an RSU (meters);
- q, which denotes the target QoS (Mbps).

In return, the *served*(.) function computes the proportion of vehicles within the RSU's communication range that can obtain their desired level of throughput, expressed by q. To do that, *served*(.) proceeds as follows. First, using Eq. 5, it verifies if the RSU located at (i, j) alone can meet the QoS demands of all the vehicles within its communication range. If so, then *served*(.) returns 1.

Otherwise, by successive iterations, it finds and returns the largest c value ($c \in [0, 1]$) such that $c \cdot \sum_{(k,l)\in range(i,j)} d_{k,l}$ vehicles obtains a throughput greater or equal to q. Note that $1 - c$ denotes the proportion of vehicles within the communication range of the RSU that are left unserved by this RSU.

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