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Geometry-Based Vehicle-to-Vehicle Channel Modeling for Large-Scale Simulation

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Abstract

Large-scale Vehicular Ad Hoc Network (VANET) simulators by and large employ simple statistical channel models. By design, such models do not account for specific objects in the region of interest when estimating the channel. While computationally efficient, these models were shown to be unable to provide satisfactory accuracy on a link level for typical VANET scenarios. Specifically, experimental studies have shown that both large static objects (e.g., buildings and foliage) as well as mobile objects (surrounding vehicles) have a profound impact on the quality of vehicle-to-vehicle (V2V) channels. While several recently proposed large-scale V2V channel models account for static objects (e.g., buildings) in the simulated area, there is a need for a comprehensive model that takes into account both the static and the mobile objects. To fill this gap, we designed a geometry-based, computationally manageable V2V channel model that uses the real-world locations and the actual dimensions of vehicles, buildings, and foliage to simulate the V2V channel more realistically. We use the outlines of the modeled objects to form spatial tree structures for efficient manipulation of geographic data. We distinguish and model separately the following three link types: line of sight (LOS), non-LOS due to vehicles, and non-LOS due to static objects. Apart from the model for large-scale signal variations, we also propose a simple model for small-scale signal variation using the number and size of the objects around the communicating vehicles. We validate the models against extensive measurements performed in urban, suburban, highway, and open space environment. We provide the complete simulation recipe for the implementation of the model in simulators. Finally, we implement the model in Matlab and show that it scales well by simulating networks with tens of thousands of objects and hundred thousand communicating vehicle pairs using commodity hardware.

Index Terms

VANET, vehicle-to-vehicle communication, simulation, signal propagation modeling, channel model

I. INTRODUCTION

Vehicular Ad Hoc Networks (VANET) research efforts have so far relied heavily on simulations, due to the prohibitive costs of deploying real world testbeds. Existing channel models implemented in VANET simulators for both vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) links are by and large simple statistical models (e.g., free space, log-distance path loss [1], etc.), which do not account for specific objects located in the simulated area. Previous studies (e.g., [2], [3]) have shown that simplified statistical channel models are unable to simulate VANET channels accurately. On the other hand, location-specific channel models, such as those based on ray-tracing [4], yield results that are in a very good agreement with the real world. However, these models are computationally too expensive to be practically useful for modeling large-scale networks in VANET simulators. Other notable problems of ray-tracing models are the need for a detailed object database and sensitivity to inaccuracies of the object database, which make it difficult to correctly predict the path of the reflecting and diffracting rays. For these reasons, ray-tracing models have not been implemented in large-scale, packet-level VANET simulators.

In this study, we aim to bridge the gap between overly simplified statistical models and computationally expensive ray-tracing models by performing location-specific channel modeling with respect to large objects in the vicinity of the communicating vehicles, at the same time limiting the calculations by using only the simple representation of the objects (i.e., their outlines). We use the real-world locations and dimensions of nearby buildings, foliage, and vehicles to determine the line of sight conditions for each link. We showed in [5] and [6] that vehicles are the most significant source of signal attenuation and variation in highway environments. In urban and suburban environments, apart from vehicles, static objects such as buildings and foliage have a significant impact on inter-vehicle communication [7]. Therefore, to enable realistic modeling in urban and suburban environments, we developed a model that incorporates static objects as well.

We first perform extensive set of measurements to prepare the ground for designing a large-scale packet-level V2V channel model. We measure the channel characteristics (received power and packet delivery rate) in a number of real-world scenarios. We perform experiments in and around Pittsburgh, PA, USA, and Porto, Portugal in distinct environments where VANETs will be deployed: highway, suburban, urban, open space, and parking lot. We characterize the impact of both mobile objects (vehicles) and static objects (buildings and foliage) on the received power, packet delivery rate, and effective range.

Next, we propose a V2V channel model that calculates the path loss deterministically using the outlines of the objects in the simulated location. Additionally, based on the location and the number of objects, the model stochastically assigns
additional small-scale signal variation on top of the path loss. The model takes into account both mobile and static objects by leveraging a limited amount of geographical information that is easily available in order to produce results comparable to those in the real world. Specifically, we use the locations of the vehicles along with the information on the location and shape of the buildings and foliage. Vehicle locations are available through either real world traces (e.g., via GPS) or traffic mobility models, whereas the building and foliage outlines and locations are freely available from projects such as the OpenStreetMap (www.openstreetmap.org). The premise of our model is that line of sight (LOS) and non-LOS (NLOS) links exhibit considerably different channel characteristics. This is corroborated by numerous experimental studies (e.g., [6], [8], [9]), which have shown that the resulting channel characteristics for LOS and NLOS links are fundamentally different. Based on these studies and by using the findings from our previous work described in [5], which identified surrounding vehicles as an important factor in V2V channel modeling, our approach is to use simple geographical descriptors of the simulated environment (outlines of buildings, foliage, and vehicles on the road) to classify V2V links into three groups:

- Line of sight (LOS) – links that have an unobstructed optical path between the transmitting and receiving antennas;
- Non-LOS due to vehicles (NLOSV) – links whose LOS is obstructed by other vehicles;
- Non-LOS due to buildings/foliage (NLOSb) – links whose LOS is obstructed by static objects (buildings or foliage).

We model each of the three link types separately; Section [IV] describes our modeling approach in detail. The model is intended for implementation in packet-level, discrete-event VANET simulators (notable examples are Jist/SWANS [10], NS-2 [11], NS-3 [12], etc.). We employ computational geometry concepts suitable for representation of geographic data required in simulating VANETs. We form a bounding volume hierarchy (BVH) structures [13], in which we store the information about outlines of both the vehicles and buildings. VANET-related geometric data lends itself to an efficient BVH implementation, due to its inherent geometrical structure (namely, relatively simple object outlines and no overlapping of building and vehicle outlines).

We validate the model against measurements and show that it successfully captures both small-scale and large-scale propagation effects in different environments (highway, urban, suburban, open space). We provide complete simulation recipe for the implementation of the model in simulators and we implement the model in Matlab. We show that the model scales well by simulating networks of different size, with up to tens of thousands of objects in the scene and hundred thousand communicating pairs. Since the model requires minimum geographic information – the location and the dimensions of modeled objects (vehicles, buildings, and foliage) – it is well suited for implementation in discrete-event VANET simulators.

The rest of the paper is organized as follows. The details of the experimental setup are shown in Section II. Section III explains the spatial tree structures we use to efficiently implement the model. Section IV describes the proposed channel model, along with the recipe for implementation of the model in VANET simulators. Results validating the proposed model against measurements are shown in Section V whereas the computational performance of the model is discussed in Section VI. Section VII describes the related work, while Section VIII concludes the paper.

II. Experiment Setup

As a baseline for the model validation and to inform the design of the model, we performed experiments in the following locations:

- Porto Downtown – 9 km route shown in Fig. I(a) going from the Paranhos parish to the Avenida dos Aliados in downtown Porto and back. Approximate coordinates (lat, lon): 41.153673, -8.609913;
- Porto Open Space – 1 km route shown in Fig. I(b) Approximate coordinates (lat, lon): 41.210615, -8.713418;
- Porto Urban Highway (VCI) – 24 km route shown in Fig. I(c) Approximate coordinates (lat, lon): 41.1050224 – 8.5661420;
- Porto Highway (A28) – 13.5 km route shown in Fig. I(d) Approximate coordinates (lat, lon): 41.22776, -8.695148;
- Porto Outlet – shown in Fig. 13(a). Approximate coordinates (lat, lon): 41.300137, -8.707385;
- Pittsburgh Suburban (5th Ave) – 7 km route shown in Fig. I(e) Approximate coordinates (lat, lon): 40.4476089, -79.9398574;
- Pittsburgh Open Space (Homestead Grays Bridge) – 2 km route shown in Fig. 11(j) Approximate coordinates (lat, lon): 40.4103279, -79.9181137).

Photographs of each of the measurement locations can be seen in Fig. 2. Measurements were performed multiple times at each of these locations. Experiments were performed between May 2010 and December 2011. Each vehicle was equipped with a NEC LinkBird-MX V3, a development platform for vehicular communications [14]. DSRC parameters are shown in Table [I]. Identical hardware setup and parameters were used in all experiments. We also performed experiments in downtown Pittsburgh. However, due to many high-rises taller than 100 meters, the GPS reception suffered from multipath that occasionally generated location errors in excess of 30 meters. Therefore, we did not include these results in our analysis. The buildings in downtown Porto are significantly lower, thus the GPS location information is more accurate.

Furthermore, we used building and vehicle outlines of the city of Porto, Portugal, described in Table [I] and freely available from the DRIVE-IN project website [16]. A snapshot of the data is shown in Fig. 4. We also used the building and foliage outlines from OpenStreetMap [17]. As of yet, for the locations where we performed the measurements, the foliage data is
TABLE I
PORTO DOWNTOWN BUILDINGS AND VEHICLE DATASET (MORE DETAILS AVAILABLE IN [15])

<table>
<thead>
<tr>
<th>City area</th>
<th># buildings</th>
<th>Area of buildings</th>
<th># vehicles</th>
<th># tall vehicles</th>
<th>Veh. density</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>41.3 km²</td>
<td>17346</td>
<td>8.6 km²</td>
<td>10566</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>595 (5.6%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>255 veh/km²</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameter</th>
<th>802.11p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channel</td>
<td>180</td>
</tr>
<tr>
<td>Center frequency (MHz)</td>
<td>5900</td>
</tr>
<tr>
<td>Bandwidth (MHz)</td>
<td>20</td>
</tr>
<tr>
<td>Data rate (Mbps)</td>
<td>6</td>
</tr>
<tr>
<td>Tx power (setting, dBm)</td>
<td>18</td>
</tr>
<tr>
<td>Tx power (measured, dBm)</td>
<td>10</td>
</tr>
<tr>
<td>Antenna gain (dBi)</td>
<td>5</td>
</tr>
<tr>
<td>Beacon frequency (Hz)</td>
<td>10</td>
</tr>
<tr>
<td>Beacon size (Byte)</td>
<td>36</td>
</tr>
</tbody>
</table>

TABLE II
HARDWARE CONFIGURATION PARAMETERS

(a) Porto Downtown.  (b) Porto Open Space.  (c) Porto Urban Highway (VCI).  (d) Porto Highway (A28).
(e) Pittsburgh Suburban.  (f) Pittsburgh Open Space.

Fig. 1. Experiment locations with indicated routes. Figures are not in the same scale.
TABLE III

DIMENSIONS OF VEHICLES USED IN THE EXPERIMENTS

<table>
<thead>
<tr>
<th>Vehicle</th>
<th>Dimensions (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Height</td>
</tr>
<tr>
<td>Portugal</td>
<td></td>
</tr>
<tr>
<td>2007 Kia Cee’d</td>
<td>1.480</td>
</tr>
<tr>
<td>2002 Honda Jazz</td>
<td>1.525</td>
</tr>
<tr>
<td>2010 Mercedes Sprinter</td>
<td>2.591</td>
</tr>
<tr>
<td>2010 Fiat Ducato</td>
<td>2.524</td>
</tr>
<tr>
<td>USA</td>
<td></td>
</tr>
<tr>
<td>2009 Toyota Corolla</td>
<td>1.466</td>
</tr>
<tr>
<td>2009 Pontiac G6</td>
<td>1.450</td>
</tr>
</tbody>
</table>

scarcely represented in the OpenStreetMap database. Therefore, the results we obtain mostly pertain to buildings and vehicles. However, as described by Wang et al. in [18], high-precision foliage maps (1m x 1m resolution) can be extracted using image classification techniques [19] on freely available aerial photography data [15], [20].

We used regular passenger cars and commercial vehicles depicted in Fig. 3. Dimensions of the vehicles are listed in Table III. All passenger cars we used have a height of approximately 1.5 meters, which coincides with the statistical mean height for personal vehicles [5], whereas both vans are approximately 2.5 meters tall.

Fig. 2. Snapshots of the experiment locations.

Fig. 3. Vehicles used in the experiments. First row: Kia Cee’d and Honda Jazz; second row: Mercedes Sprinter and Fiat Ducato; third row: Toyota Corolla and Pontiac G6.
Before we discuss the structure of our channel model, we introduce the spatial tree structure used for efficient VANET object manipulation. For a description of the modeled area, we use the outlines of buildings and foliage available through free geographic databases such as OpenStreetMap [17]. Such sources of geographical descriptors have become available recently, with a crowdsourced approach to geographic data collection and processing. Apart from the outlines of buildings and foliage available in such databases, we use the locations of the vehicles, which can be obtained through GPS logs, vehicular mobility model, or aerial photography [15]. Similarly, the dimensions of vehicles can be drawn from statistical distributions [5] or aerial photography [15].

In networks with hundreds (or thousands) of vehicles, checking whether two nodes can communicate using a naïve approach (i.e., checking each node against each other node) is computationally too expensive. Therefore, in order to model large networks, efficient data structures are required. Based on the outlines of the objects, we form bounding volume hierarchy (BVH) structures [13]. BVH is a tree structure in which objects in the field are structured hierarchically based on their location in space. VANET-related geometric data lends itself to an efficient BVH implementation, due to its inherent geometrical structure (namely, relatively simple, non-overlapping object outlines). More specifically, we utilize R-trees (where R stands for “rectangle”, since it is used as the bounding shape) [21] to store the vehicle, building, and foliage outlines. R-trees are often used to store spatial objects (streets, buildings, geographic regions, counties, etc.) in geographic databases. Even though they do not have good worst-case performance [9] in practice they were shown to have good tree construction and querying performance, particularly when the stored data has certain properties, such as limited object overlap [22]. Figure 4 shows the outlines of the vehicles and buildings, obtained through aerial photography [15], which we use as the input for our model. We utilize R-trees to store the vehicle, building, and foliage outlines. We store vehicle outlines in a separate R-tree. The main difference in storing the outline of vehicles when compared to buildings and foliage is that, unlike vehicles, buildings and foliage do not move, therefore the model only needs to compute their R-tree once, after which it does not change. On the other hand, the vehicle R-tree changes at each simulation time-step. Figure 5 shows the BVH built on the outlines of vehicles in the city of Porto for one time snapshot obtained through aerial photography.

We construct each tree using a top-down approach, whereby the algorithm starts with all objects (i.e., vehicles, buildings, or foliage) and splits them into child nodes (we use binary R-tree, i.e., each non-leaf node has two child nodes). To keep the tree balanced, we sort the current objects at each node splitting based on the currently longer axis so that each created child node contains approximately half of the objects. We note that similar tree data structures, such as k-d tree and quadtree/octree, could be used instead of R-tree, with consideration to the specific application at hand and limitations and advantages of a specific data structure (for details, see de Berg et. al [23]).

When bounding rectangles of all objects overlap in a single point/area, the operation of checking the object intersection is quadratic in the number of objects in the R-tree (i.e., it is the same as the naïve approach that checks for intersection of every object with every other object). However, such extreme situations do not occur when modeling vehicular environments.
IV. DESCRIPTION OF THE CHANNEL MODEL

We designed a model that, in addition to the LOS component, incorporates the following propagation effects (shown in Fig. 6): 1) transmission (propagation through material); 2) diffraction; and 3) reflection. We focus on modeling the impact of vehicles, buildings, and foliage (as opposed to smaller objects such as traffic signs, traffic lights, etc.) for two reasons. First, on highways, obstructing vehicles are the most important objects for modeling the V2V channel, as the roads are predominantly straight and the largest portion of communication happens over the face of the road [5]. In urban areas, obstructing vehicles have a significant impact for communicating pairs that are on the same street [6]. Furthermore, the 2-D nature of the roads in suburban and urban areas implies that communication also happens outside the road surface. In such cases, static obstructions such as buildings and foliage play an important role [24], [25]. Buildings and foliage are the main source of obstructions for communication on the intersections and across different streets [7], whereas buildings and vehicles are the main sources of reflections and diffractions [26]. Furthermore, other static objects such as lamp posts, street signs, railings, etc., are neither readily available in geographic databases, nor would it be computationally feasible to model them due to their number, shape, and size.

We validate the model against a set of experiments performed in different environments. Based on the measurements, we limit the complexity of the geometric model to a point where it represents well the real world, but requires orders of magnitude less computations than complex ray-tracing models (as discussed in detail in Section VI).

A. Classification of link types

As mentioned previously, we distinguish three types of links: 1) line of sight (LOS); 2) non-LOS due to vehicles (NLOSv); and 3) non-LOS due to buildings/foliage (NLOSb). Using the insights from measurements we performed in different environments (Section II), we apply different propagation models for each of the three link types. Table IV shows the employed models. Specifically, through measurements in open space, urban, suburban, and highway environments, as well as by consulting the existing V2V measurements (e.g., [6], [27]), we concluded that LOS links are well approximated with a two-ray ground reflection model. Similarly, the NLOSv links are well modeled using the vehicles-as-obstacles model we proposed in [5]. Finally, for NLOSb links, we calculate single-interaction reflections and diffractions to account for the “around the corner”
TABLE IV

MODELS USED FOR DIFFERENT LINK TYPES

<table>
<thead>
<tr>
<th>Link Type</th>
<th>Propagation Mechanisms</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOS</td>
<td>Two-ray ground [1] &amp; fading (Section IV-F)</td>
</tr>
<tr>
<td>NLOSv</td>
<td>Vehicles-as-obstacles [5] &amp; fading (Section IV-F)</td>
</tr>
<tr>
<td>NLOSb</td>
<td>Reflections and diffractions (Section IV-D) &amp; log-distance path loss &amp; fading (Section IV-F)</td>
</tr>
</tbody>
</table>

communication, and log-distance path loss [1] for cases where single-interaction rays are either non-existent or carry low power. We elaborate on the propagation mechanisms used for each of the three link types in more detail in Sections IV-D, IV-E, and IV-F.

B. Rules for reducing the computational complexity of the model

As shown in the Fig. 6, in addition to the LOS signal component, we model the following propagation effects: 1) transmission (propagation through material); 2) diffraction; and 3) reflection. However, if we were to calculate all significant rays between the transmitting and receiving vehicle, the model would not be different from the existing ray-tracing models (e.g., [4], [28]). Therefore, we exploit additional information available in VANETs, along with the specific and known geometric properties of the environment, to improve the performance of the model and make it suitable for implementation in large-scale, packet-level VANET simulators. Specifically, we implement the following rules.

1) Apart from checking which objects are blocking the LOS of the link and classifying the link into LOS, NLOSv, or NLOSb category, the model searches for the objects inside the ellipse shown in the Fig. 4. These objects are later used to calculate both small- and large-scale signal variations.

2) To calculate the small-scale signal variations, we use the number, relative location, and density of potentially reflecting and diffracting objects (other vehicles, buildings, foliage) around the communicating pair. We discuss the implemented model in detail in Section IV-F.

3) For each link, we first check the blockage of LOS by buildings and foliage. If there is LOS blockage, we do not check the vehicle R-tree for LOS blockage, since obstructing buildings and foliage reduce the power at the receiver considerably more than obstructing vehicles (see, e.g., [6], [7], [25], [29]). For links whose LOS is not blocked by buildings or foliage, we check the R-tree containing vehicles.

4) R-trees enable efficient intersection testing and neighbor querying [21]. Apart from using R-trees for link type classification, to determine reflected and diffracted rays, we use them to efficiently implement a variation of the method of images [30, Chap. 7] – a technique used to geometrically determine the reflected and diffracted rays.

5) For LOS, NLOSv, and NLOSb links, we define the maximum communication range \( r \) as shown in Fig. 4 which determines the threshold distance above which the received power is assumed to be insufficient to correctly decode the message at the receiver, irrespective of the channel conditions. Specifically, we define \( r_{\text{LOS}} \), \( r_{\text{NLOSv}} \), and \( r_{\text{NLOSb}} \) for LOS, NLOSv, and NLOSb links, respectively. In general, these radii are functions of transmit power, receiver sensitivity, antenna gains, and the surrounding environment. For a given set of radio parameters (reception threshold, transmit power, etc.), the ranges can be obtained either through field measurements or analytically.

6) We used the insights from the experiments to refine the model. Specifically, we tested the benefits we obtain when considering reflections and diffractions for each of link types (LOS, NLOSv, and NLOSb). As we will show in Section V, the comparison between the model employing path loss propagation mechanisms shown in Table IV and the measurement results for LOS and NLOSv links showed a good match. Furthermore, adding reflections and diffractions resulted in minimal benefits in terms of accuracy, while incurring a high computational overhead. On the other hand, for NLOSb links, reflected and diffracted rays, particularly single-interaction rays, account for a significant portion of the received power in V2V communication (e.g., see [31]). Therefore, we explicitly model the single-interaction reflections and diffractions for NLOSb links only.

C. Transmission through Foliage

For foliage, we use the attenuation-through-transmission model based on the measurements described in [29], [32], [33]. Specifically, we use the empirically-derived formulation from [32], where attenuation for deciduous trees is calculated per meter of transmission using

\[
MEL = 0.79 f^{0.61},
\]

where \( MEL \) is mean excess loss per meter of transmission through trees and \( f \) is frequency in GHz [33]. For DSRC frequency centered at 5.9 GHz, this results in attenuation of 2.3 dB per meter of transmission through trees, which is in line with the
measurement results in the 5.85 GHz band reported in [29]. Similar calculations can be performed for coniferous trees as well as for seasonal changes when trees are not in full foliage [32]. Decision on which kind of trees to model (deciduous or coniferous) and the level of foliage (e.g., due to the time of the year) needs to be determined for the location where the simulations are carried out. Geographic databases such as OpenStreetMap allow for specification of such characteristics [17]; provided that the different types of vegetation are tagged properly, they can be distinguished and modeled accordingly. Finally, we do not model any reflections or diffractions off foliage (i.e., only transmission attenuation is accounted for); rather, we implicitly encompass their scattering effects in the subsequent small-scale signal variation calculations.

D. Combining multiple paths: E-field and received power calculations

Once all contributing rays (LOS, reflected, and diffracted) have been calculated, we determine their contributions in terms of the E-field and the received power for each link. We obtain the resultant E-field envelope as follows [1, Chap. 3.]:

$$|E_{TOT}| = |E_{LOS} + \sum_j E_{Refl_j} + \sum_k E_{diffr_k}|,$$

(2)

where $E_{LOS}$, $E_{Refl}$, and $E_{diffr}$ are E-fields of line of sight, reflected, and diffracted rays, respectively. Expanding eq. 2, we get

$$|E_{TOT}| = \frac{E_0 d_0}{d_{LOS}} \cos \left( \omega_c \left( t - \frac{d_{LOS}}{c} \right) \right) + \sum_j R_j \frac{E_0 d_0}{d_j} \cos \left( \omega_c \left( t - \frac{d_j}{c} \right) \right) + \sum_k D_k \frac{E_0 d_0}{d_k} \cos \left( \omega_c \left( t - \frac{d_k}{c} \right) \right),$$

(3)

where $\frac{E_0 d_0}{d_{LOS}}$ is the envelope E-field at a reference distance $d_0$, $\omega_c$ is the angular frequency ($\omega_c = 2\pi f$), $t$ is the time at which the E-field is evaluated, $d_x$ represents distance traversed by ray $x$, $R_j$ is the reflection coefficient of reflected ray $j$, and $D_k$ is the diffraction coefficient of diffracted ray $k$. When the originating medium is free space, the reflected coefficient $R$ is calculated as follows for vertical and horizontal polarization, respectively [1, Chap. 3.]:

$$R_{||} = -\frac{\epsilon_r \sin \theta_i + \sqrt{\epsilon_r - \cos^2 \theta_i}}{\epsilon_r \sin \theta_i + \sqrt{\epsilon_r - \cos^2 \theta_i}},$$

(4)

and

$$R_{\perp} = \frac{\sin \theta_i - \sqrt{\epsilon_r - \cos^2 \theta_i}}{\sin \theta_i + \sqrt{\epsilon_r - \cos^2 \theta_i}},$$

(5)

where $\theta_i$ is the incident angle and $\epsilon_r$ is the relative permittivity of the material.

Regarding diffractions, we do not calculate the diffraction coefficient directly; we approximate the E-field for diffracted rays using the knife-edge model [34]. However, the model contains all the geographical information to calculate the diffraction parameter for single diffractions using uniform theory of diffraction (UTD) [35].

The ensuing received power $P_r$ (in watts), assuming unit antenna gains, is calculated as follows:

$$P_r = \frac{|E_{TOT}|^2 \lambda^2}{480\pi^2},$$

(6)

where $\lambda$ is the wavelength. Note that $P_r$ accounts for the slow fading signal component of LOS links, whereas for NLOSv and NLOSb links there are also contributions in terms of multipath generated by multiple diffractions around vehicles in case of NLOSv (horizontal and vertical multiple knife-edge diffractions) and single-interaction reflections and diffractions in case of NLOSb.

Furthermore, in cases where the accuracy of the geographic database is not sufficiently high for correct calculation of the phase shift – this might often be the case for DSRC systems, since the wavelength is approximately 5 cm, thus requiring centimeter-grade database precision – the phase shift component in the eq. 3 for different incoming rays can be approximated using a distribution that represents the given environment well (e.g., uniform in case of isotropic scattering or based on the predominant angles of arrival in case of non-isotropic scattering [36], [37]).

E. Practical considerations for different link types and propagation mechanisms

1) LOS communication: For LOS links, we implement the complete two-ray ground reflection model given by the following equation:

$$|E_{TOT}| = \frac{E_0 d_0}{d_{LOS}} \cos \left( \omega_c \left( t - \frac{d_{LOS}}{c} \right) \right) + R_{ground} \frac{E_0 d_0}{d_{ground}} \cos \left( \omega_c \left( t - \frac{d_{ground}}{c} \right) \right),$$

(7)
Fig. 7. Snapshot of a simulation in downtown Porto with reflections and diffractions shown for randomly selected communication pairs. Objects in the scene: buildings (black lines), vehicles (blue lines), reflected rays (green dashed lines), diffracted rays (magenta dash-dotted lines). Note that tall vehicles (elongated blue pentagons) obstruct reflected and diffracted rays, as they are most often taller than 60% of the first Fresnel zone for the antennas of the communicating vehicles. Short vehicles block the reflected/diffracted rays less frequently.

where the reflection coefficient $R_{\text{ground}}$ and distance $d_{\text{ground}}$ for the ground-reflected ray are calculated according to the exact antenna heights (i.e., we do not assume that the distance between transmitter and receiver is large compared to heights of the vehicles, as is often done in simulators [11], [12]). As will become apparent from our results (Section V), using the exact height of the antennas is important, since even a centimeter-grade difference in height of either Tx or Rx results in significantly different interference relationship between the LOS and ground-reflected ray.

In calculating $R_{\text{ground}}$, we model the relative permittivity $\varepsilon_r$ to obtain the “effective” range of the reflection coefficient for the road. It was pointed out in [38] that the idealized two-ray model is an approximation of the actual V2V channel, since the reflection coefficient is affected by the antenna location, diffraction over the vehicle roof below antenna, and the roughness of the road, among others. Therefore, we set the $\varepsilon_r$ value used to generate the LOS results to 1.003, as this value minimized the mean square error for Porto Open Space dataset (see Section V). Then, we use the same $\varepsilon_r$ value for LOS links in all environments. Similar concept of effective reflection coefficient range calculation was used in [27] and [38].

2) Reflections: With respect to the reflection coefficients off building walls, we apply similar reasoning on the “effective” range of reflection coefficients as with the two-ray ground reflection model. We match the reflection coefficient distribution to the values empirically derived by Landron et al. in [39], where the authors extract the reflection coefficients for brick building walls from controlled measurements. In the locations where we performed measurements (Fig. 7), the buildings were predominantly made of brick and concrete.

The reflections are calculated off buildings and vehicles. Since all buildings are significantly taller than any vehicle, any building can reflect the signal for any communicating pair. On the other hand, in order to be a reflector, a vehicle needs to be taller than both communicating vehicles’ antennas, since otherwise the reflected ray does not exist. In practice, this means that reflecting vehicles are predominantly tall ones. Furthermore, as can be seen in Fig. 7 tall vehicles are more likely to block reflections coming off the building walls or other vehicles, whereas short vehicles are less likely to do so, since they are less likely to be taller than the height of the line between the communicating antennas discounted for the 60% of the first Fresnel zone.

3) Diffractions: For diffractions off buildings and vehicles, we use the (multiple) knife-edge diffraction. In case of vehicles, diffractions are calculated for both the vertical plane (i.e., over the vehicle roofs) and the horizontal plane (on the sides of the vehicles). In case of buildings, diffractions are calculated in the horizontal plane only (we assume that the buildings are too tall for diffraction over the rooftops). In all cases, we perform the multiple knife-edge diffraction as described in [34].

4) Log-distance path loss in deep-fade areas: Reflections and diffractions off buildings and vehicles are used for NLOSb links. We limit the calculation of diffracted and reflected rays to single-interaction (single-bounce) rays, except for multiple diffraction due to vehicles. It was recently shown by Abbas et al. in [31] that single-interaction reflections and diffractions are most often the dominating propagation mechanisms in the absence of LOS. The authors conclude that “single-bounce reflections with static objects e.g., buildings, roadsigns, and streetlights, often are the dominating propagation mechanisms for V2V links in the absence of line of sight whereas the reflections from other vehicles contribute little unless these vehicles are tall enough.” Similar findings are reported by Paier et al. in [40]. By determining the LOS conditions and modeling LOS and single-interaction rays, we aim to design a model that accounts for the most important rays, at the same time keeping the
However, communicating pairs that are not located on the same street or adjacent orthogonal streets (e.g., vehicles in parallel streets with contiguous buildings between the streets or vehicles several streets apart) most often do not have strong single-interaction reflected or diffracted rays, but are still occasionally able to communicate. For such communicating pairs, multiple interaction reflections and scattering are the dominant contributors of power at the receiver \[30\]; calculating such rays incurs prohibitively high computations and a geographical database with a high level of detail. Furthermore, our measurement results and those reported in similar studies (e.g., \[9, 24, 25\]) show that communication range in NLOSb (i.e., building-obstructed) conditions using DSRC radios operating in the 5.9 GHz frequency band is limited to approximately 200 meters, even with the maximum transmit power allowed by the standard \[41\]. Thus, in order to avoid costly geometric computations which predominantly yield power levels below reception threshold, at the same time allowing for communication in deeply faded areas, we determine the received power as follows. We calculate the received power using both the single-interaction diffractions and reflections through the described model and using the log-distance path loss model \[30\]. The log-distance path loss \(PL\) (in dB) for distance \(d\) is given by \[30\]:

\[
PL(d) = PL(d_0) + 10\gamma \log_{10} \left( \frac{d}{d_0} \right),
\]

where \(\gamma\) is the path loss exponent and \(PL(d_0)\) is the path loss at a reference distance \(d_0\). For the log-distance path loss model, the received power \(Pr_{PL}\) (in dB) at a distance \(d\), assuming unit antenna gains, is given by

\[
Pr_{PL}(d) = Pt - PL(d),
\]

where \(Pt\) is the transmitted power in dB.

In our simulations, we used \(\gamma = 2.9\), which we extracted from the Porto urban dataset for the NLOSb conditions where there were no significant single-interaction reflections/diffractions. Previous studies reported similar values: \(\gamma = 2.9\) by Durgin et. al in \[29\] (NLOSb environment) and \(2.44 \leq \gamma \leq 3.39\) by Paschalidis et al. in \[42\] (urban environment – various LOS conditions). Finally, for NLOS links, we determine the received power as the maximum of the received power calculated by the implemented model (using eq. \[6\] in dB) and the log-distance path loss (eq. \[9\]):

\[
Pr_{NLOS} = \max(Pr, Pr_{PL}).
\]

### F. Small-scale signal variations

The model described above captures signal variations at different scales for different link categories. For LOS links, the model accounts for large-scale signal variation due to distance and ground-reflection. NLOSv and NLOSb links, on the other hand, are by definition obstructed (“shadowed”), albeit at different levels of obstruction within each category: 1) in case of NLOSv, a small or a large blocking vehicle, or one or more vehicles; 2) in case of NLOSb, deep or slight building or foliage obstruction. Thus, for NLOSv and NLOSb links, the variation captured by the proposed model accounts for shadowing variation as well as part of fast fading as follows. For NLOSv links, multiple diffraction paths around vehicles are accounted for (i.e., one path over the vehicle roofs and two potential paths on the sides of the vehicles). For NLOSb links, the multipath is partially accounted for by calculating the single-interaction reflections and diffractions. Therefore, the model accounts for the most significant rays in case of all three types of links (LOS, NLOSv, and NLOSb). To account for additional (smaller scale) signal variation inherent in V2V communication (e.g., due to scattering and higher order diffractions and reflections), using the insights obtained through experiments, we designed a small-scale signal variation model that captures the richness of the propagation environment surrounding the communicating pair. We first characterize the small-scale signal variations in the collected measurements; next, we design a simple model for small-scale variation that complements the previously described components of the model that deal with large-scale signal variations.

1) **Small-scale variations in the experimental datasets:** We used the collected measurements to characterize small-scale variation in different LOS conditions, environments, and with different levels of vehicular traffic (i.e., temporal variation). For each collected measurement, we separate the data into LOS, NLOSv, and NLOSb category using the videos recorded during the experiments. Then, we divide the collected data into two-meter distance bins. We selected two meter bins because they are small enough not to incur significant distance-related path loss dependence, at the same time containing enough data points to allow for a meaningful statistical characterization. Figure 8 shows the distribution of received power for two-meter distance bins. For the LOS datasets, the normal distribution seems to fit the data reasonably well, with a better fit for the open space environment LOS data (Fig. 8(a)) than the urban LOS data (Fig. 8(b)) due to the richer reflection environment in the case of the latter. Normal fit for the NLOSv and NLOSb data is less accurate due to the variety of conditions that are encompassed by the data (e.g., different number of obstructing vehicles in case of NLOSv, deep or slight building obstruction in case of NLOSb, a small or a large blocking vehicle, or one or more vehicles; 2) in case of NLOSb, deep or slight building or foliage obstruction. Thus, for NLOSv and NLOSb links, the variation captured by the proposed model accounts for shadowing variation as well as part of fast fading as follows. For NLOSv links, multiple diffraction paths around vehicles are accounted for (i.e., one path over the vehicle roofs and two potential paths on the sides of the vehicles). For NLOSb links, the multipath is partially accounted for by calculating the single-interaction reflections and diffractions. Therefore, the model accounts for the most significant rays in case of all three types of links (LOS, NLOSv, and NLOSb). To account for additional (smaller scale) signal variation inherent in V2V communication (e.g., due to scattering and higher order diffractions and reflections), using the insights obtained through experiments, we designed a small-scale signal variation model that captures the richness of the propagation environment surrounding the communicating pair. We first characterize the small-scale signal variations in the collected measurements; next, we design a simple model for small-scale variation that complements the previously described components of the model that deal with large-scale signal variations.

The model is easily extensible to (recursively) account for the higher order interactions, however at a prohibitively increasing computational cost. Furthermore, an increasingly detailed geographical database is required in order to model higher-order interaction rays correctly.
LOS data from Porto Open Space dataset with best-fit normal distributions.

LOS data from Porto Urban dataset with best-fit normal distributions.

LOS data from Porto Urban dataset with best-fit normal distributions.

NLOSb data from Porto Urban dataset with best-fit normal distributions.

NLOSv data from Porto Urban dataset with best-fit normal distributions.

Fig. 8. Cumulative distribution functions of the received power for two-meter distance bins. All plotted bins contain at least 40 data points. For LOS (Figs. 8(a) and 8(b)), and NLOSv data (Fig. 8(c)), the bins are centered at decades from 10 to 100 meters (i.e., the curves represent the following bins, left to right: [99-101], [89-91], ..., [9-11] meters). For NLOSb data (Fig. 8(d)), due to lack of data points at lower distances, the two-meter bins centered at the following distances are shown (left to right): 90, 85, 70, 65, 60, 55, 50, 45, and 15 meters. All plots are for passenger (short) vehicle experiments.

Based on the measured data, we choose to use normal distribution to describe the small-scale variation process in all three LOS conditions. Therefore, the empirically determined small-scale variation is a zero-mean normal distribution $N(0, \sigma)$ (normal in dB; log-normal in terms of power in watts).

2) Accounting for additional small-scale signal variation: Apart from establishing the distribution of signal variation, we also need to determine its parameter – i.e., the standard deviation ($\sigma$) of the normal distribution – since different environments and LOS conditions experience different levels of signal variation, as shown in Fig. 8. Therefore, we implement a simple model that accounts for the additional small-scale fading due to the objects in the area around the communicating pair as follows. Using the communication ellipse for each pair as explained in Fig. 4, we count the number of vehicles and sum the area of static objects in the ellipse. We chose the area of the static objects, rather than their number because, unlike the size of vehicles, their area varies greatly (see Fig. 4). Since a large-area building/foliage is more likely to impact the communication than a smaller one, we use their area instead of their number in the calculations. In terms of different link types, the objects in the ellipse have the following effects: 1) for the communicating pairs located on the same street (i.e., LOS or NLOSv links), the objects inside the ellipse will include the vehicles along that street and buildings and foliage lining the street – arguably, these are the most important sources of scattering, diffractions, and reflections that generate multipath fading for such links (see Fig. 7); 2) similarly, for NLOSb links (i.e., links between vehicles on different streets and with buildings/foliage blocking the LOS), the ellipse will include buildings, foliage, and vehicles that generate significant reflecting, diffracting, and scattering rays (Fig. 7).

Next, we set the minimum and maximum $\sigma$ for a given LOS condition based on the collected measurements. We do not extract the minimum and maximum $\sigma$ for each experiment location, since we aim to determine a single pair of values for each of the three LOS environments (LOS, NLOSv, and NLOSb), which could then be used across a number of different locations. Therefore, we utilize minimum and maximum $\sigma$ as calculated from the experiments and shown in Table V. For simplicity, we use a single pair of minimum/maximum values for both short and tall vehicles. The minimum $\sigma$ for NLOSv and NLOSb links is set to zero, since the most significant reflected and diffracted rays for these links are already accounted. For LOS links, on the other hand, we calculate the minimum $\sigma$ from the least variable environment in terms of small-scale fading (i.e., the

This is in line with the results reported by recent V2V experimental studies described in [25] and [43].
open space). The maximum values for all three link types have been taken as the most variable fading environment from the collected datasets. By averaging $\sigma$ for all two-meter bins with more than 40 samples in that dataset, we obtained the values shown in Table V. Note that minimum and maximum $\sigma$ values can be different for other environments; however, we believe the values we obtained are sound guidelines, since they are similar to small-scale variation observed in other experimental studies (e.g., [25], [43]).

To calculate the small-scale signal deviation $\sigma$ (in dB) for the communication pair $i$, $\sigma_i$, we define the following expression:

$$\sigma_i = \sigma_{\text{min}} + \frac{\sigma_{\text{max}} - \sigma_{\text{min}}}{2} \cdot \left( \sqrt{\frac{N_V}{N_V_{\text{max}}}} + \sqrt{\frac{A_S}{A_S_{\text{max}}}} \right),$$

where $\sigma_{\text{min}}$ is the minimum small-scale signal deviation (in dB) for $i$’s LOS type (LOS, NLOSv, or NLOSb), $\sigma_{\text{max}}$ is the maximum deviation value for $i$’s LOS type, $N_V$ is the number of vehicles per unit area in $i$’s ellipse, $N_V_{\text{max}}$ is maximum number of vehicles per unit area, $A_S$ is the area of static objects per unit area in $i$’s ellipse, and $A_S_{\text{max}}$ is the maximum area of static objects per unit area. The value of $N_V_{\text{max}}$ can be calculated a priori from historical data (e.g., maximum number of vehicles per area in a given city or a highway), whereas $A_S_{\text{max}}$ can be calculated from geographical databases, such as [17]. In our calculations, we used $N_V_{\text{max}}$ and $A_S_{\text{max}}$ derived from the Porto dataset, with references defined on a square kilometer (i.e., maximum number of vehicles and maximum area of static objects in a square kilometer). For each of its constituents (vehicle-induced and static objects-induced signal variation), equation (11) is essentially a square interpolation between minimum small-scale variation in an environment (e.g., open space without any objects other than communicating vehicles) and maximum variation (e.g., the downtown of a city during rush hour with a high density of vehicles and buildings/foliage). As shown in eq. (11) and due to the lack of a better classification, we give equal weights to the number of vehicles and the area of static objects when calculating the small-scale variation. Finally, once the $\sigma$ is calculated for a given communication pair, we add a normally distributed random variable $N(0, \sigma)$ to the previously calculated received power (eq. (9)):

$$P_{r_{TOT_i}} = 10 \log_{10}(Pr_i) + N(0, \sigma_i).$$

G. Channel Model Simulation Structure

Figure 9 shows the simulation execution flowchart of the model. In the flowchart, we synthesize the large-scale and small-scale model, apply the rules for reducing the complexity of the model, and show how the R-tree structures are used. The flowchart contains the information required to implement the proposed model in discrete-event packet-level VANET simulators. We discuss implementation of the model in more details in Section VI.

H. Assumptions

Since we are designing a large-scale channel model with a specific application in mind – V2V communication using IEEE 802.11p (DSRC) radios [41] or a similar technology – we rely on several IEEE 802.11p protocol characteristics in order to simplify the implementation of the model. Additionally, here we list other assumptions and simplifications we made when designing the model.

1) IEEE 802.11p has been designed to cope with severe channel conditions [8]. The channel bandwidth (10 MHz), symbol length (8 $\mu$s), guard time (1.6 $\mu$s), and Adjacent Channel Rejection (ACR) have all been designed so that the multipath fading/Doppler spread and Inter-Symbol Interference (ISI) do not affect the communication even in the harshest channel conditions [41]. In combination with Orthogonal Frequency-Division Multiplexing, it is envisioned to enable flat fading and ISI-free channels. For this reason, in our model we assume that the channel coherence bandwidth is sufficiently high so as not to cause frequency selective fading on OFDM subcarriers. Experimental studies by Acosta-Marum and Ingram in [44] and by Paier et al. in [26] confirm this assumption. However, a recent study by Fernandez et al. in [45] points out that the proposed IEEE 802.11p physical (PHY) layer can suffer high packet error rates in highly-faded V2V environments, particularly due to suboptimal equalization. In case the PHY layer of IEEE 802.11p is unable to cope with channel variations, thus resulting in packet errors, the results generated by the proposed model would represent an upper bound on the performance in terms of packet delivery rate.

<table>
<thead>
<tr>
<th>LOS Condition</th>
<th>$\sigma_{\text{min}}$ (source)</th>
<th>$\sigma_{\text{max}}$ (source)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOS</td>
<td>3.3 dB (Porto Open space)</td>
<td>5.2 dB (Porto Urban)</td>
</tr>
<tr>
<td>NLOSv</td>
<td>0 dB</td>
<td>5.3 dB (Porto Urban)</td>
</tr>
<tr>
<td>NLOSb</td>
<td>0 dB</td>
<td>6.8 dB (Porto Urban)</td>
</tr>
</tbody>
</table>
For current Tx-Rx pair
NLOSb link
Calculate reflections off buildings and vehicles in ellipsoid
Calculate diffractions off buildings in ellipsoid
Calculate $P_r$: received power based on reflections and diffractions
Calculate $P_{rc}$: received power based on log-distance path loss
Rec. power = max$(P_r, P_{rc})$

NLOSv link
Calculate and add small scale signal variation based on objects in ellipsoid and link type

Start Simulation
Yes

Static objects exist?
No
Create (or load previously stored) Building/Foliage R-Tree

For current time step
Create Vehicle R-Tree

For current Tx-Rx pair
Get vehicles in ellipsoid
Get area of building/foliage in ellipsoid

Are buildings or foliage blocking LOS?
Yes
NLOSb link
No

Are vehicles blocking LOS?
Yes
NLOSv link – calculate rec. power using (multiple) knife edge
No
LOS link – calculate rec. power using two-ray ground

Processed all Tx-Rx pairs for current time step?
No
Processed all time steps?
Yes
End Simulation

Fig. 9. Channel model simulation flow.
<table>
<thead>
<tr>
<th>Link Type</th>
<th>Max. comm. range</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r_{LOS} ) - urban</td>
<td>500</td>
</tr>
<tr>
<td>( r_{LOS} ) - outside urban</td>
<td>1000</td>
</tr>
<tr>
<td>( r_{NLOS_v} )</td>
<td>400</td>
</tr>
<tr>
<td>( r_{NLOS_b} )</td>
<td>300</td>
</tr>
</tbody>
</table>

2) We limit the calculation of diffracted and reflected rays for NLOSb links to single-interaction (single-bounce) rays. It was recently shown in [31] and [40] that single-interaction reflections and diffractions are most often the dominating propagation mechanisms in the absence of LOS on urban intersections. However, even though communicating vehicles in parallel streets with contiguous buildings between the streets or vehicles several streets apart most often do not have strong single-interaction reflected or diffracted rays, they might be able to communicate. For this reason, we implement the log-distance path loss to compensate for the lack of higher-order reflections and diffractions.

3) We assume that buildings are too tall for any meaningful amount of power to be received over them. Since even the shortest buildings are at least 5 meters taller than the vehicles, simple calculations using knife-edge diffraction [34] show that the losses due to diffraction over the rooftops is in excess of 30 dB (with 40+ dB loss for buildings 15 or more meters taller than vehicles), thus making the power contribution over the rooftops negligible.

4) Currently, vehicles, buildings, and foliage are accounted for in our model. In environments where other objects have a significant impact (e.g., lamp posts, signs, railing, etc.), the model would need geographical information about these objects as well. However, such objects are currently not readily available in geographic databases. Furthermore, the additional gains in realism need to be compared against the increase in the computational complexity due to the additional objects, particularly if the number of such objects is large.

5) Due to the limited precision of the databases and the focus on packet-level simulation, we do not model scattering. Because of their potentially large number, scattering objects could significantly increase the complexity of the calculations that need to be performed by the model. Additionally, the precision of such calculations would be questionable.

6) Due to the wavelength used by DSRC radios (approx. 5 cm), in case when the geographical databases are inaccurate, the calculations of the incoming phase of the reflected/diffracted ray might be erroneous, thus randomly combining constructively or destructively at the receiver. As noted earlier, in such cases, depending on the antenna design and the environment, the phase shift can be approximated by either uniform phase (in case of isotropic scattering) or based on the predominant angles of arrival in case of non-isotropic scattering [36], [37].

7) Currently, we assume that the terrain is flat. For locations with significant elevation changes, the model would need to be adapted so that the elevation is included, provided such data is sufficiently accurate.

V. Results

In this section we show the measurements and channel prediction results for the measurement locations shown in Figs. 1 and 2. In the model, we use the GPS locations of the vehicles recorded during measurements to simulate the channel in the same locations where the communication occurred. We use the actual dimensions of the vehicles (Table III) and the corresponding static objects extracted from geographical databases. Furthermore, we use the communication ranges specified in Table VI. These values are based on our own measurements, as well as results previously collected in [6], [7], [24], [25]. Note that \( r_{LOS} \) was set to 1000 meters outside urban areas and 500 meters in urban areas, whereas we use the same values of \( r_{NLOS_v} \) and \( r_{NLOS_b} \) in all environments.

Figure 10 shows the received power for a 30-minute experiment conducted on a 10 km route in downtown Porto, Portugal (Fig. 2(a)), along with the results generated by the model. Using the recorded videos of the experiments, we separated the data into three link types: LOS, NLOSv, and NLOSb. This allowed us to evaluate the ability of the model to simulate each link type. Since we extracted the small-scale variation from the measured datasets, we consider that the best performance the model can have in terms of small-scale variation is bounded by the empirically measured small-scale variation for the given link type. In other words, the performance of the employed (stochastic) small-scale model is upper-bounded by the measured small-scale variation. Therefore, for all results henceforth, apart from the mean difference in terms of received power between measured and modeled results, we also report the standard deviation around the mean (i.e., the standard error of the model).

It is important to note that the mean and standard error of the model are calculated on a per-packet basis; for each collected measurement datapoint, we calculate the mean and standard deviation using the per-packet received power difference between the model and experiments. Furthermore, we use the same value of relative permittivity (\( \varepsilon_r=1.003 \)) in all environments to calculate the reflection coefficient for the ground reflection (i.e., we do not fit the value to a given dataset).
A. LOS Links

Figure 11 shows the results for the LOS data in different environments. The model fits the experimental data quite well in all environments, with the mean difference between model and measurements within 0.6 dB for each of the environments. Similarly, the standard error for all LOS datasets (shown in a text box in each of the subfigures of Fig. 11) is within 0.5 dB of the measured small-scale signal variation for that dataset (noted in the caption of each subfigure). Regarding the open space LOS results, we attribute the higher fading of the Pittsburgh Open Space dataset (Fig. 11(c)) compared to the Porto Open Space dataset (Fig. 11(b)) to the guard rails and metal fence (visible in Fig. 2(f)), which did not exist in the Porto Open Space location (Fig. 2(b)). The daytime Pittsburgh Suburban measurements (Fig. 11(e)) and Porto Urban measurements (Fig. 11(f)) have a significantly richer reflection/diffraction/scattering environments due to the nearby vehicles in case of the former and both vehicles and buildings in case of the latter. This results in the increase of both the small-scale variations ($\sigma$) and the standard error.

B. NLOSv Links

Figure 12 shows the results for the NLOSv data in different environments and with both passenger (short) and tall vehicles. The model fits the experimental data well in all environments, with the mean difference between model and measurements within 1.3 dB in each of the environments. Again, the standard error for NLOSv datasets (shown in a text box in each of the subfigures of Fig. 12) is within 0.9 dB of the small-scale fading of that dataset (noted in the caption of each subfigure). It is interesting to see that NLOSv results for tall vehicles (vans) experience both lower fading and lower standard error. This is due to the advantageous position of the antennas on top of the vans, which experience fewer significant reflected, diffracted, and scattered rays than the antennas on the shorter vehicles, thus resulting in a more stable channel.

C. NLOSb Links

Figure 13(a) shows the Porto Outlet location with the overlaid reflecting and diffracting rays as generated by the model. Once the vehicles are not in LOS, the predominant propagation mechanisms become single-interaction reflections and diffractions. Figure 13(b) shows distinct transitions in the received power as the vehicles go from LOS to NLOSb conditions. The model is able to capture the steep drop in the received power once the LOS is obstructed by building. At the same time, the log-distance path loss, because it is unable to capture the transition between LOS and NLOSb, underestimates the received power in LOS conditions and overestimates it in NLOSb conditions. This result highlights the importance of location-specific, link-level channel modeling: the transition between different LOS conditions, which exhibit considerably different characteristics, can only be performed by taking into account the objects in the specific location. On the other hand, models relying on the common parameters of an environment (such as the overall path-loss exponent in the case of log-distance path loss) are unable to model such transitions, which results in “averaging” of the received power between different LOS conditions. While such averaging does not have a significant effect on the overall distribution of the received power, for these models to be useful in calculation of channel characteristics for a specific link over time, our results show that, at a minimum, the different LOS conditions need to be identified and modeled separately.

Previous measurement studies concluded that, for communication in the 1 to 6 GHz frequency band, transmission through buildings does not play as important role as reflections and diffractions around buildings. For example, Anderson in [35]...
Fig. 11. LOS data - model vs experimental measurements. Figure (a) shows the raw data collected through measurements and generated by the model. Figures (b) through (f) show the mean and the standard deviation around the mean received power for two-meter distance bins. Results are plotted only for bins with at least 40 data points. Error bars represent one standard deviation around the mean received power calculated for each distance bin separately. All results show the data collected with passenger (short) vehicles. The results with tall vehicles (vans) exhibited similar behavior.
Fig. 12. NLOSv data - model vs experimental measurements. Figures show the mean and the standard deviation around the mean received power for two-meter distance bins. Results are plotted only for bins with at least 40 data points.
(a) Reflections (green lines) and diffractions (magenta) generated by the model and overlaid on the image of the Porto Outlet location. The vehicles started close to each other with clear LOS and slowly moved along paths indicated by the arrows, thus going from LOS to NLOS conditions. During the measurements, the two large buildings that create reflections and diffractions were the only large protruding objects in the scene, with clearance in excess of 100 meters to the nearest objects (i.e., there were no parked vehicles). Coordinates of the location: 41.300137, -8.707385

(b) Transition of the model between LOS and NLOS conditions at the Porto Outlet location for a single 30-second run. The distinct conditions are annotated. The outliers in the top right corner are due to GPS inaccuracy while vehicles were stationary. For comparison, we plot the log-distance path loss for the same location.

Fig. 13. Porto Outlet experiment.

Fig. 14. NLOSb data - model vs measurements for Porto Downtown location using passenger vehicles. Figure shows raw data collected in the measurements and generated by the model. Measured averaged $\sigma$: 6.8 dB.

performed experiments at 1.8 GHz and modeled the diffraction and reflection around an isolated building corner using uniform theory of diffraction (UTD). The author concluded that through-wall transmission is negligible compared to the corner diffraction and wall reflections. Durgin et. al in [29] performed experiments at 5.85 GHz and pointed out that “transmission through the house was not as important as outdoor multipath scattering”. Similarly, our results showed a good match between the experiments and the model including reflections and diffractions only (see, e.g., Fig. 15). For this reason, we do not consider the through-building transmission as an important effect and therefore do not include it in our model.

Figure 14 shows NLOSb data for the experiments performed in downtown Porto. The difference between the model and experiments is higher than in the case of LOS and NLOSv (mean difference is -1.6 dB, and the standard deviation is 7.6 dB). The increased disparity is due to two reasons: 1) the variety of communication scenarios encompassed by NLOSb data is higher (e.g., slight obstruction by a building corner, deep obstruction by an entire building, obstruction by foliage, etc.), resulting in a standard deviation of the measured received power of 6.8 dB (considerably higher than LOS and NLOSv); and 2) along the measurement route, there was occasional foliage which was not recorded in the geographical database, thus it was not modeled.

The packet delivery rate for the experimentally obtained NLOSb data between 150 m and 500 m was below 15% (i.e., more than 85% of the packets were not received when the communicating vehicles were more than 150 m apart). Additionally,
during experiments, only decodable data was recorded (i.e., only packets received above the reception threshold of -92 dBm were recorded). This made it impossible to compare the results generated by the model with the measurement data below the reception threshold. For these reasons, we compare the model to the experiments for the NLOSb data below 150 m.

D. Combined large-scale and small-scale signal variation

Figure 15(a) shows the signal variation around the mean for the model and measurements. For each two-meter bin, the variation is a composite result generated by the large-scale model (that also includes a part of small-scale effects through single-interaction reflections and diffractions) with the addition of the zero-mean, normally distributed variable with standard deviation $\sigma$ determined using eq. 11 that represents the additional small-scale (multipath) variations. The model generates the overall signal variation comparable to that obtained through measurements, with the variation across the distance bins for both the model and the measurements of approximately 6.3 dB. This result shows that the implemented small-scale model can capture the fast-varying signal changes in vehicular environment by considering the objects surrounding the communicating pair.

Figure 15(b) shows the value of $\sigma$, i.e., the additional small-scale signal variation (eq. 11) as generated by the model. The value of $\sigma$ is comparatively lower for the NLOSv and NLOSb links, since the variation generated by the most significant reflected and diffracted rays is already included in the large-scale model. Unlike the data generated by the model, in the measurement data we have no way of distinguishing the signal variation generated by the large-scale and small-scale effects (apart from splitting the links in LOS, NLOSv, and NLOSb categories). However, we know that for the LOS links, the only deviation from the theoretical two-ray ground reflection model is generated by $\sigma$, therefore the per-bin average $\sigma$ in Fig. 15(b) is higher than in case of NLOSv and NLOSb, where the signal variation is generated by both $\sigma$ and the large-scale model.

VI. A Few Notes on the Performance of the Model

We implemented the described model in MATLAB. We were able to simulate the entire city of Porto, with an area of approximately 41 km$^2$ containing 10566 vehicles and 17346 static objects, using off-the-shelf hardware (2011 MacBook Air) and the communication ranges shown in Table VI. Figure 16 shows the processing times for the most salient parts of the model. Figure 16(a) shows the complete time it takes to determine channel conditions for 10000 links and varying network sizes. By increasing the network size (i.e., the number of objects in the scene), the processing time increases linearly even for the largest network size with more than 28000 objects. Figure 16(a) also shows separately the time to perform the most computationally intensive operation: calculating reflections and diffractions. Across different network sizes, calculating reflections and diffractions (which are calculated for NLOSb links only) accounts for two-thirds of the computation time. For this reason, we plan to explore if comparably realistic results can be obtained for NLOSb links without explicitly calculating the reflections and diffractions (e.g., by utilizing a log-distance path loss with appropriate exponent).

Figure 16(b) shows that the R-tree construction scales linearly with the number of objects that need to be stored in the tree. The results for constructing vehicle and static object R-trees are similar, since it takes only marginally more time to fit the more complex static objects (outlines of buildings/foliage) in the minimum bounding rectangles. After that stage, the calculations per object are identical. Figure 16(c) shows the increase in link classification time when the network size (and therefore, the vehicle and static R-tree size) increases. Again, the increase is linear with the size of the network.

Network simulators need to account for interference from neighboring communicating pairs. In order to calculate Signal to Interference plus Noise Ratio (SINR), signal contributions from all currently transmitting neighboring vehicles need to be taken
Fig. 16. Calculation times for various parts of the model on the downtown Porto dataset. We used the following hardware: 2011 MacBook Air, 1.7GHz Core i5, 4 GB RAM. The complete dataset contains 10566 vehicles and 17346 static objects over 41 km². For simulations on smaller networks (first three data points in subfigures (a), (b), and (c)), we used half, quarter, and eighth of the entire city area, which contained corresponding number of vehicles and static objects. All results are for single-core operation (i.e., no parallelization).

into account. Depending on the employed medium access protocol, this might imply calculating a large number of parallel and interfering transmissions from neighbors. For example, time and frequency division protocols will on average result in low interference, whereas random access protocols (such as the default medium access scheme of IEEE 802.11p – CSMA/CA [41]) will generate higher interference, and thus higher number of links that need to be taken into consideration. This implies that, to calculate the SINR for a link, the interference from a relatively large number of active neighboring links might also need to be calculated. However, with regards to per-link processing time, Fig. 16(d) shows that, for a fixed network size, increasing the number of links results in a linear increase of processing time with a mild slope (e.g., to classify 5000 links, it takes 1.1 second, whereas for 100000 links it takes 3.1 second). Therefore, the additional burden due to calculating the power from nearby interfering links is not overly high for the proposed model.

Furthermore, it has to be noted that, from the computational complexity point of view, selecting the correct communication range if quite important. Increasing the range results in quadratic increase in the number of objects that need to be analyzed for a given communication pair. By design, in the extreme case, if the communication range is equal to the size of the simulated area, the number of neighboring objects (and therefore calculations) is quadratic with the number of communicating pairs. Therefore, the communication range for each of the LOS types needs to be carefully chosen so that it is minimized while accounting for potentially communicating pairs.

With regards to the scalability of the model, the trends shown in Fig. 16 are far more important than the actual processing times. The result show linear behavior even for large networks comprising tens of thousands of objects and communicating pairs. We also point out that the operations required by the model (R-tree construction and classification of links through object querying and intersection tests) can inherently be parallelized. Since the model relies on geometric manipulations of the objects that impact the channel, analogies can be made to computer graphics problems, where parallel rendering techniques are utilized to perform occlusion/visibility and intersection testing. Parallelization techniques can be employed in both the object querying and intersection testing, as well as the R-tree construction. Since there is no dependency between different communication pairs (links), parallelizing the computations across different links is straightforward. Furthermore, recent advances in parallel R-tree construction, querying, and intersection testing (e.g., see Luo et. al in [46]) indicate that significant speed increase can be obtained by using multicore graphics processing units.
Several recent studies tackled efficient and realistic simulation of vehicle-to-vehicle channels in different VANET environments. Karedal et al. in [7] and Mangel et al. in [47] designed channel models focused on street intersections, where buildings create non-LOS (NLOSb) conditions. Both studies selected representative urban intersections and performed measurements which were then used to design channel models and calibrate the path loss and fading parameters. Karedal et al. in [57] designed a V2V channel model based on measurements performed in highway and suburban environment at the 5.2 GHz frequency band. The model distributes the vehicles and static objects randomly and analyzes four distinct signal components: LOS, discrete components from vehicles, discrete components from static objects, and diffuse scattering. Based on the measurements, the authors propose a set of model parameters for highway and suburban environment. While it enables modeling of different propagation characteristics (path loss, multipath, Doppler spread, etc.), the proposed model assumes the LOS component exists, therefore it does not specify how to determine the LOS conditions of the channel and the transitions between LOS, NLOSv, and NLOSb. Figure [15] shows that modeling the transitions between the LOS conditions is essential for obtaining realistic results, since the ensuing path loss is the most important component in determining the received power and, consequently, the decodability of the packet.

Sommer et al. in [48] performed measurements and used them for calibrating a computationally efficient path loss model aimed at distinguishing between the LOS and NLOSb conditions. In case of NLOSb, the model calculates the received power based on the length of transmission through buildings and the number of walls through which the transmitted ray travels, while diffracted and reflected rays are not accounted for. Conversely, empirical studies reported by Anderson in [35] and Durgin et al. in [29] concluded that reflections and diffractions are the dominant propagation mechanisms for NLOSb links in the 1.9 GHz and 5.9 GHz frequency bands, whereas transmission through buildings was found not to contribute considerably.

In terms of channel modeling on a city-wide scale, studies reported by Giordano et al. in [49] and Cozzetti et al. in [50] focus on computationally efficient channel modeling in grid-like urban environments, where streets are assumed to be straight and intersecting at a right angle. While such assumptions hold for certain urban areas, in others they might oversimplify the reality (e.g., in the city of Porto – Fig. 4).

With regards to improving the channel modeling using location-specific information, Wang et al. in [18] utilize aerial photography to determine the density of scatterers in the simulated area. By processing the aerial data to infer the scatterer density, the authors determine the fading level for a given location on the road.

A number of studies were performed in various VANET environments to estimate the channel by performing measurements and fitting the measured data using well-known models (e.g., log-distance path loss [30]). For example, Paschalidis et al. in [42] performed measurements in different environments (urban, suburban, rural, highway) and fitted the measurements data to the log-distance path loss model. The path loss exponent (PLE) varied considerably (between 1.83 and 3.59) for different locations and LOS conditions. The large range of PLE values goes to show that a single PLE value can not capture the characteristics of a channel, even for a single location/environment. Therefore, different LOS conditions (LOS, NLOSv, NLOSb) need to be distinguished and modeled separately.

When it comes to evaluating the impact of vehicular obstructions, several experimental studies emphasized the importance of obstructing vehicles. Gallagher et al. in [51] quantified the impact of vehicular obstructions on different parameters, such as packet reception, throughput, and communication range. Interestingly, Gonzalvez et al. in [52] performed experiments where the impact of vehicular traffic and tall vehicles (buses) also heavily influenced the vehicle-to-infrastructure (V2I) links, despite the roadside units being placed at elevated positions (between 3 and 10 meters) next to or above the roads. Tall vehicles decreased the effective communication range by 40%, whereas the dense traffic reduced the range by more than 50%.

The studies above were aimed at measuring the channel characteristics and fitting the channel models to the already collected measurements. However, research aimed at incorporating the vehicles in the channel model and therefore predicting their effect has been scarce. Apart from our previous work reported in [5], to the best of our knowledge, there have only been two studies aimed at explicitly introducing vehicular obstruction in channel modeling. Abbas et al. in [43] performed V2V measurements and showed that a single vehicle can incur more than 10 dB attenuation, which is in line with the results reported in [5]. Based on the measurements, the authors designed a stochastic channel model for highway environments that incorporates vehicular obstructions and determines the time duration of LOS, NLOSv, and NLOSb states using the measured probability distributions of each state. Wang et al. in [53] perform isolated (“parking lot”) measurements and characterize the loss due to vehicles obstructing the LOS. Furthermore, they model the loss due to vehicles by employing a three-ray knife-edge model, where diffraction loss is calculated over the vehicles and on the vehicle sides. Their results show a good agreement between the isolated measurement results and the proposed method.

VIII. CONCLUSIONS

We proposed a computationally efficient channel model that can be used in large-scale packet-level VANET simulators. Compared to the simple statistical channel models currently used in VANET simulators, the proposed model utilizes the geographic descriptors to enable location-specific modeling of the V2V channel. Furthermore, the time-dependent component
of the channel is accounted for: depending on the density of the vehicles in an area, the channel between two vehicles can change considerably as the surrounding vehicles create LOS obstructions, reflections, and diffractions. Compared to the ray-tracing methods, the model is beneficial in terms of: 1) computational complexity, since it performs only a subset of complex calculations required for full ray-tracing models; and 2) reduced requirements for geographical information – the required information is limited to outlines and types of buildings and foliage, and locations and dimensions of vehicles, which are readily available through geographical databases and mobility traces.

Furthermore, with limited (and often imperfect) geographical description of the simulated area, there is a point of diminishing returns in terms of simulation realism, where a marginal improvement in the realism requires a large computational effort. For this reason, we used VANET-specific information (e.g., the number of surrounding objects, the dimensions of objects and their propagation characteristics, etc.) to limit the complexity of the model. To enable a more efficient channel modeling, we divided the links into three categories: 1) line of sight (LOS); 2) non-LOS due to vehicles (NLOSv); and 3) non-LOS due to buildings/foliage (NLOSb). The results regarding LOS and NLOSv conditions shown in figs. [1] and [2] indicate that, in order to correctly model LOS and NLOSv scenarios, it is sufficient to consider the main type of propagation mechanism for the respective link type (specifically, two-ray ground reflection model for LOS and vehicles-as-obstacles model for NLOSv [5]), with additional small-scale signal variation proportional to the number of vehicles and the area of static objects (buildings, foliage) in the communicating pair’s ellipse (as defined in Fig. [1]). This allows for an efficient implementation in the simulation environments, as the required calculations are limited to LOS classification and determining the number and area of objects in the communication pair’s ellipse, both of which can be performed efficiently using spatial data structures, such as R-trees. On the other hand, for NLOSb links, it is beneficial to consider reflections and diffractions as the main propagation mechanisms, since they enable a better estimation of the received power, particularly when vehicles are communicating “around the corner” (i.e., where vehicles are on two sides of a corner of a single building, as shown in Figs. [3(a) and [3(b)]. However, since reflections and diffractions accounted for two thirds of the computation time for the model, as part of our future work we will look for comparably accurate, but less computationally expensive techniques for modeling NLOSb links.

Finally, we implemented the model in Matlab and showed that it can be used to simulate networks with thousands of communicating vehicles across different environments (highway, suburban, urban). The model scales linearly with the increase of both the network size (i.e., the number of objects in the simulation) and the number of communicating pairs.

REFERENCES


