A Stochastic Performance Model For Dense Vehicular Ad-Hoc Networks

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***Abstract*—Network level modeling of vehicular networks usually takes one of two paths. Either a mobility simulator is used to generate vehicular movement traces, combined with a network simulator to simulate packet transmissions. Or, simple stochastic assumptions, such as Poisson Point Processes and Manhattan Grids are imposed to allow analytical modeling. In this paper, we use the combination of mobility and network simulations to derive more accurate analytical models for vehicular ad-hoc networks in dense urban scenarios. Our results show that cars tend to group in clusters with approximately exponential geometric densities. Furthermore, we demonstrate that the process of interference in a dense network can be accurately modeled based on a linear function of the numbers of neighbors, as well as a Gamma distributed random process.**

***Index Terms*—Performance Modeling, V2X, Hidden Node Interference**

I. Introduction

The widespread distribution of Vehicular Ad-Hoc Networks (VANETs) will be a consequence of the adoption of autonomous vehicles and their requirement for more complex services. In order to estimate the performance of the resulting VANETs, the communication has be to modeled as accurate as possible, especially given the fact that for ad-hoc networks, the node configuration has a large impact on the network quality. Frequently, the modeling approach for VANETs is based on mobility simulations, for example Simulation of Urban Mobility (SUMO) [1], in combination with network simulators such as NS-3 or OMNET++. These tools, although highly valuable, have two limitations: They strongly simplify the underlying physics [2], and the resulting geometric distribution of the vehicles is difficult to grasp analytically, as street layouts are highly irregular, and driver behavior is governed by many influences that are not uniform. Hence, when analytical approaches are chosen, they are often approached with simplified assumptions. One of the most popular ideas is to treat the vehicles as a Poisson Point Process (PPP) either along a straight line, or in 2 dimensions, resulting in uniformly distributed vehicles along the line [3], [4]. This approach is based on infinitely long streets and homogeneous traffic, which can be found most pronouncedly on highways. However, even there, the model has been challenged [5], because of the inherently inhomogeneous vehicle distributions. Advances have been made to incorporate more inhomogeneous vehicle distributions into the analytical models [6], but very few comparisons between analytical models and mobility simulations exist. Furthermore, packet error models are often simplistic in their approach. Research is conducted to more accurately model packet error performance by incorporating more aspects of the underlying physical channel [7]–[10], however, none consider packet loss due to interference.

A. Our Contribution

In this paper, we present a method to derive accurate analytic abstractions from large scale simulations. On the one hand, we present a way to find matching geometrical vehicle distributions from cars based on communication parameters, on the other hand we present a straightforward modeling approach for hidden node interference. To achieve this, we employ SUMO [1], to simulate vehicular traffic in the city of Prishtina in Kosovo. The map data is retrieved from OpenStreetMap [11]. We then use the Vehicles in Network Simulations (VEINS) extension to the OMNET++ network simulator [12] to generate ad-hoc Vehicle-to-Vehicle (V2V) communications. In Section II, we describe the corresponding simulation setups. With these parameters, we then analyze the distribution of communication neighbors a node sees, and demonstrate in Section III that the common assumption of PPPs is not a good assumption, and instead propose a an approach that is based on inhomogeneous distributions. Finally, in Section IV, we analyze the packet loss due to interference of hidden nodes [13], and present our results that for the given simulation results, interference traffic can be straightforwardly modeled using a Gamma distribution and a linear-affine function.

II. System Model

The performance in dense vehicular networks is governed by the receiver quality, the single link channel conditions, and the pattern of simultaneously transmitted interfering packets on the other hand. We follow this split by considering mobility simulations, network simulations and link level models. Our goal here is to find models for packet loss due to interference, hence we do not consider packet loss caused by unfavorable channel conditions. Instead, we assume packets within communication range to be lost only if interference is present, allowing us to cleanly capture this effect.

We base the subsequent analysis on the workings of Wireless Access in Vehicular Environments (WAVE) / European

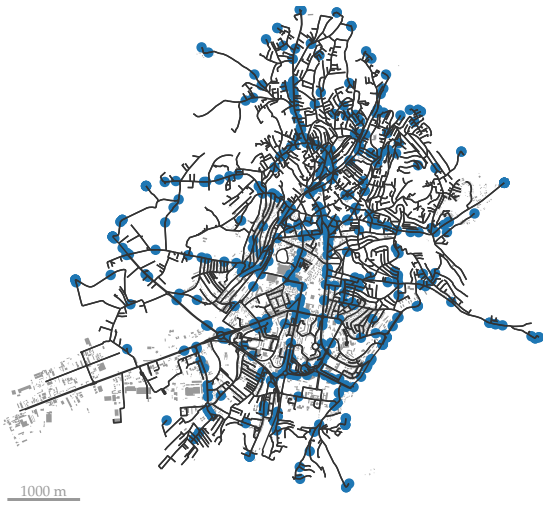


Fig. 1. Map of Prishtina with simulated vehicles shown in blue.

Telecommunications Standards Institute Intelligent Transport Systems (ITS) at 5.9 GHz (ETSI ITS-G5) [14] which are both based on IEEE 802.11p, however, analogous analysis can be straightforwardly extended to other protocols.

A. System Level Simulations

To generate high-density traffic patterns, we use the mobility simulator SUMO [1] in combination with the vehicular network extension VEINS of the network simulator OMNET++ [12]. We use the city of Prishtina as example (Figure 1), and generate mobility simulations. We generate a total simulation of 10000 s, and use the vehicle placements between seconds 5000 and 6000. This approach provides us with a stationary process that avoids the ramp-up and ramp-down of the mobility simulation. Based on these mobility simulations, we use VEINS to generate Base Safety Message (BSM) beacons at a rate of 10 Hz. These are meant to represent the baseline vehicular safety communication, resulting in a baseline channel load. Immediate channel access due to an incident will be faced with this baseline communication by the other traffic participants. The full list of parameters is shown in Table I.

TABLE I
SYSTEM LEVEL SIMULATION PARAMETERS

SUMO Parameters	Value
City Map	Prishtina, Kosovo
Nr. Vehicles	{4000, 4500, 5000}
Simulation duration [s]	10000
Analyzed simulation time [s]	5000 – 6000
VEINS Parameters	**Value**
Message type	BSM
Packet Size	200, 500
Message frequency [s^{-1}]	10
MCS	QPSK, Rate 1/2

B. Link Level Performance

Similar to [2], we use Karedal's pathloss model to calculate communication ranges [15]. Since the standard defines a range of possible transmission powers spans a large range [16], we choose 10 dBm for our analysis. Furthermore, we assume a receiver sensitivity of −88 dBm. Depending on the noise level, these parameters provide a sensing range of $r_s \sim 350$ m. If two nodes are within sensing range, they see each others transmissions, but don't necessarily decode them correctly. For this paper, we assume perfect reception within sensing range, unless a hidden node interferes. This choice is made to isolate the effect of hidden nodes from other packet error causes.

III. GEOMETRIC DISTRIBUTION

Our first analysis is based on the SUMO simulations in Prishtina. Given the maximum sensing range of Section II-B, we are interested in 2 metrics: the number of potential communication partners in range, denoted the neighbors N, and the *overlap* between a node and its neighbors. Given that $\mathcal{N}_i$ is the set of neighbors of node i, and node j is a neighbor of i then the overlap from i to j is calculated as

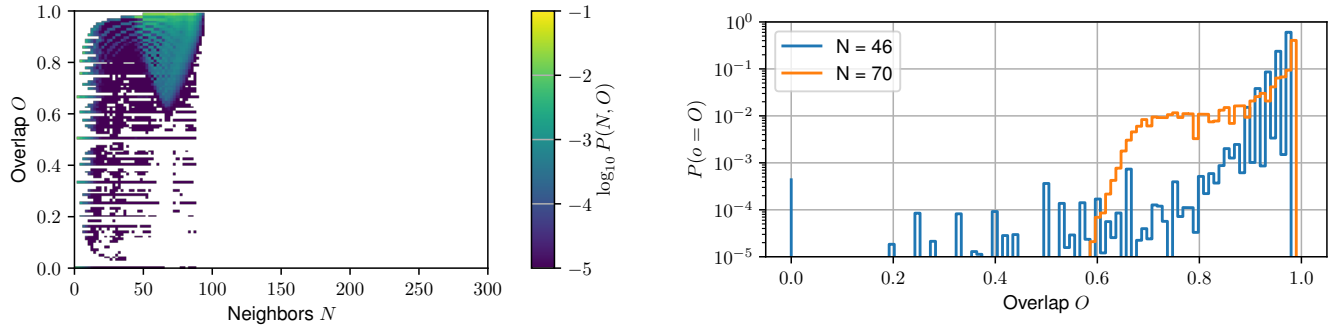
$$O(i;j) = \frac{|\mathcal{N}_i \cap \mathcal{N}_j|}{|\mathcal{N}_i|}, \tag{1}$$

where $|\cdot|$ is the magnitude of the set. This measure is not symmetric, since i and j may have a different number of neighbors. Figure 2 shows the analysis for 2 simulation setups, for 4000 and 5000 vehicles total. On the left, the joint pmf of overlap and neighbor count is displayed, while on the right the conditional pmf of the overlap for certain neighborhood counts is displayed.

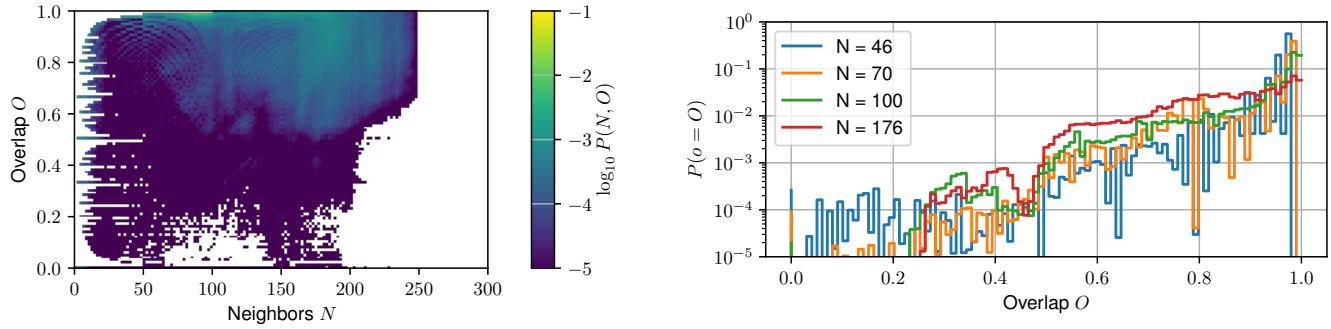
The plots illustrate that the neighborhood counts depend strongly on the traffic congestion. In the first scenario, most vehicles have between 50 and 100 neighbors, while in the second, the neighborhood count is spread up to 250 vehicles. The conditional pmfs also illustrate that the common assumption of a uniformly distributed vehicles along the streets does not match closer inspection, as a uniform vehicle distribution would result in a uniform overlap distribution between 0.5 and 1. Indeed, most of the simulation does not have uniformly loaded streets, but rather congested clusters. If we instead assume the vehicle density to be Laplacian around the congestion center 0, then the distribution equals

$$f(x;\lambda) = \frac{1}{2\lambda}\exp\left(-\frac{|x|}{2\lambda}\right). \tag{2}$$

Figure 3 shows simulated overlap pmfs for a straight street with 100 bins with vehicles being uniformly distributed, and Laplacian for different ratios of $\frac{\lambda}{r_s}$. The figure shows that for ratios larger than 1, the exponential decays so slowly that the overlap distribution approaches the uniform, while for ratios smaller than 1, there is a distinct difference. Comparing the simulation results with the synthetic data, modeling the vehicular density as Laplacian clusters fits much better, especially for lower densities. Only for very densely loaded streets ($N \gg 100$), the pmfs start to approach a uniform distribution.



(a) 4000 vehicles total.



(b) 5000 vehicles total.

Fig. 2. Joint pmf of neighborhood overlap O and numbers of neighbors N (left), as well as conditional pmfs for certain neighborhood sizes. The results are shown for 2 SUMO configurations.

Otherwise, a Laplacian distribution with a $\frac{\lambda}{r_s}$ between 0.25 and 0.35 is a much better fit.

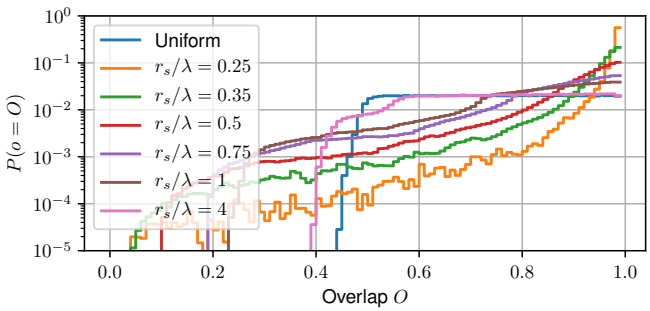


Fig. 3. Overlap distributions for Laplace distributed nodes for different ratios of sensing range and distribution decay.

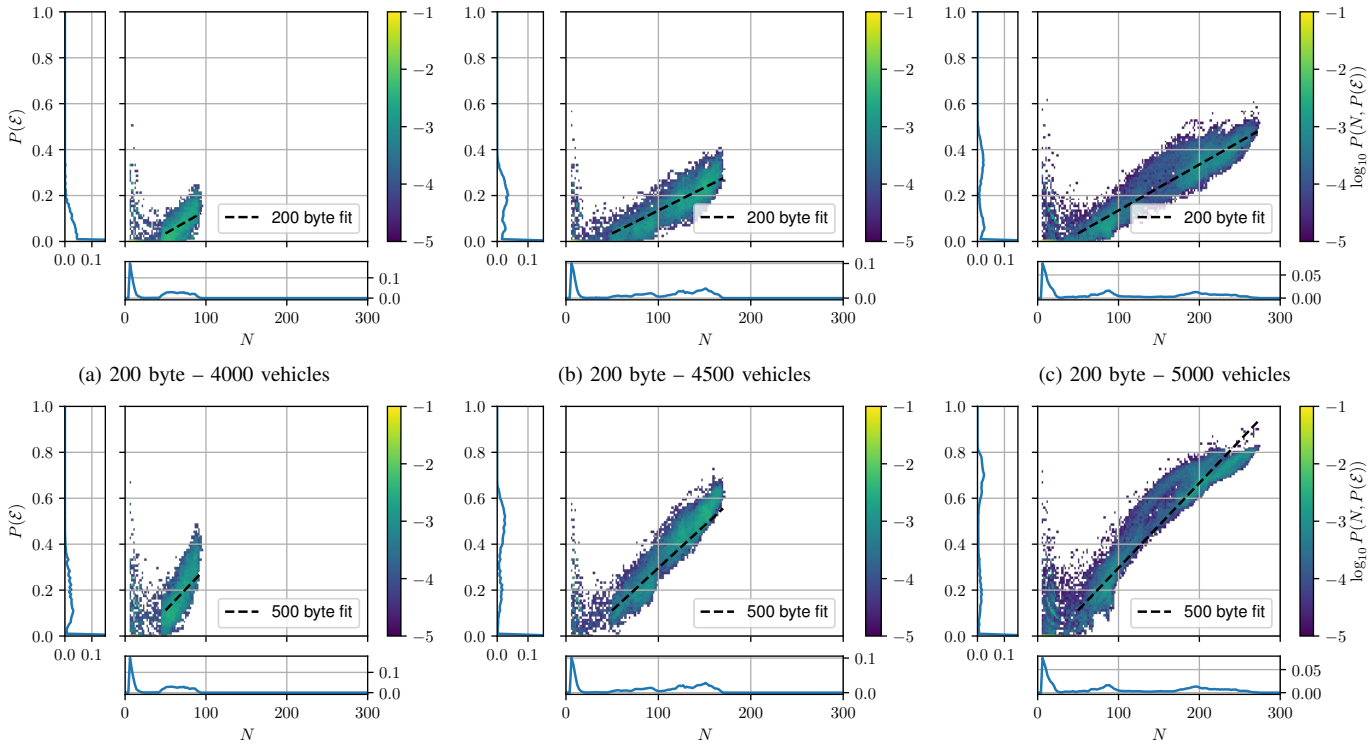
IV. Performance Model

The output of the system level simulations according to the description in Section II is shown in Figure 4 for 200 byte packets and for 500 byte packets. We show the results for 4000, 4500, and 5000 vehicles in the simulation, as these parameters resulted in suitable congestion properties for dense networks. The marginal distribution of the number of neighbors show that the neighbor distribution is not spread out equally, instead, there are, depending on the general density, two or three configurations that occur with high frequency.

Overall, results below 50 neighbors are very sparse, and scattered. This is caused by the fact that for larger vehicle loads, the vehicles tend to cluster on main streets, and not spread out over the map. Thus, we define *dense* neighborhoods as having *at least* 50 neighbors, and subsequently only consider these regions. In this dense region, it is apparent that there is an approximately linear relationship between packet loss caused by interference and neighborhood size. This is a result of the fact that the Channel Busy Ratio (CBR) is a linear function of the neighborhood size [17], and the packet loss due to interference in turn depends on the CBR. Thus, we use all generated measurement configurations, and calculate a least-squares estimate of th the mean packet $\hat{\mu}$ loss for different packet sizes as a linear-affine function of N

$$\begin{aligned} \hat{\mu}_{200}(\mathcal{E}; N) &= 0.002N - 0.065 \\ \hat{\mu}_{500}(\mathcal{E}; N) &= 0.0037N - 0.0735 \end{aligned} \tag{3}$$

These estimates are shown as dashed lines in Figure 4. While the fit is only drawn up to the final data point, it is always the same respective curves per packet size as given in Equation (3). The 200 byte results show good agreement with the linear fits up to high neighborhood numbers. The 500 byte results fit very well at the most occurring clusters below 100 and at 180 – 200 neighbors, but other influences can be seen. For example a bimodal trend at 150 vehicles is visible, as well as a saturation at 80 % packet error. We now filter this linear trend from the packet error model. We do this by taking the



(a) 200 byte – 4000 vehicles (b) 200 byte – 4500 vehicles (c) 200 byte – 5000 vehicles

(d) 500 byte – 4000 vehicles (e) 500 byte – 4500 vehicles (f) 500 byte – 5000 vehicles

Fig. 4. Joint pmf of number of neighbors and packet error ratio for different simulation configurations.

single realizations of packet loss of node i, $P_e[i]$, and remove the mean estimate depending on the number of neighbors of i, $N[i]$ as

$$\bar{P}_e[i] = P_e[i] - \hat{\mu}(N[i]) \tag{4}$$

However, negative probabilities are not meaningful, thus we shift this normalized values such that the smallest occurring value is 0

$$P'_e[i] = \bar{P}_e[i] - \min_i \bar{P}_e[i] \tag{5}$$

After these normalizing steps, the histograms of $P'_e[i]$ for 200 and 500 byte packets are shown in Figure 5. These resulting parameters can be approximated very well with a Gamma distribution

$$f(x; k, \theta) = \frac{1}{\Gamma(k)\theta^k} x^{k-1} e^{-\frac{x}{\theta}}, \tag{6}$$

as is shown with the fitted pdfs of the Gamma distribution. Thus, we present a simple model for interference-caused packet loss as function of the neighborhood size and the packet size B:

$$\mathcal{E}(B, N) = a \cdot N + b + X, \tag{7}$$

where a and b are constants and X is a Gamma-distributed random variable with shape k and scale θ, with the parameters being shown in Table II. The performance of these models are show in Figure 6. The absolute difference of the estimated mean and variance are shown to the simulated values. For 200 byte packets, the mean is estimated consistently within 5 % of the actual value, and for most values of N it is

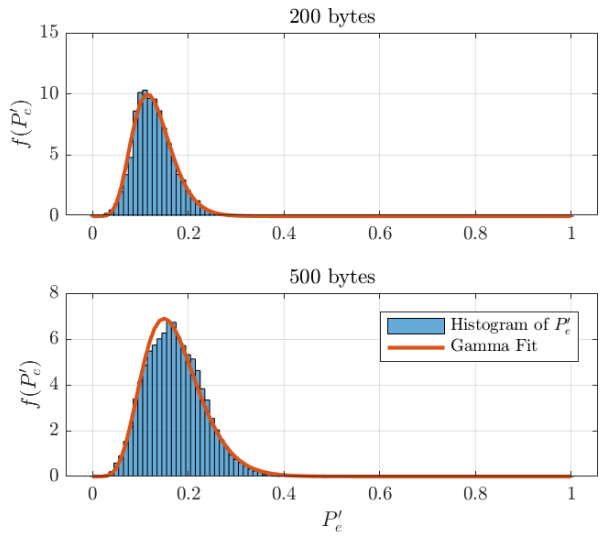


Fig. 5. Histogram of P'_e and Gamma distribution fits for 200 and 500 byte packets.

TABLE II
STOCHASTIC MODEL PARAMETERS

200 byte		500 byte	
a	0.0020	a	0.0037
b	0.0639	b	0.0979
k	9.462	k	7.85
θ	0.0136	θ	0.022

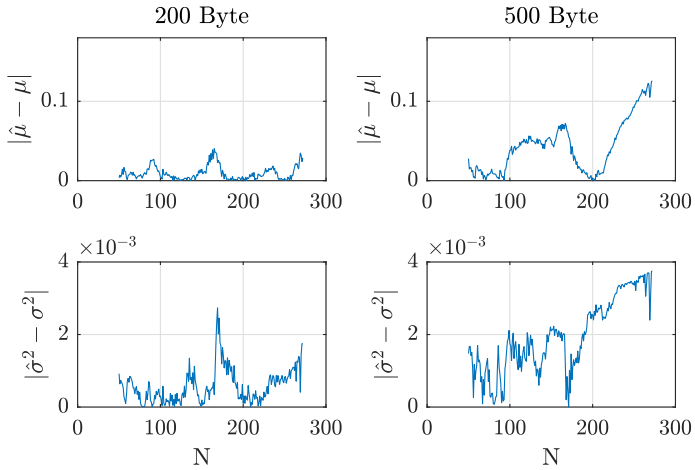


Fig. 6. Estimation performance of the Gamma-distributed fits.

significantly lower. For 500 byte packets, the values tend to be higher, but in the most frequent neighborhood sizes (below 100 or at 200), the values are again small. A similar trend is shown for the estimated variance. When calculating the expected value across all neighborhood sizes, the overall mean deviation becomes $|\hat{\mu} - \mu| = 0.0085$ for 200 byte packets, and 0.0252 for 500 byte packets. Similarly, the overall deviation of the estimated variance becomes $5.3 \cdot 10^{-4}$ for 200 byte and $1.5 \cdot 10^{-3}$ for 500 byte packets.

V. Conclusions

Our analysis shows that typical assumptions, such as uniform vehicle distributions, or absence of interference are dangerous assumptions and often misused. When using a mobility simulator is impractical, modeling vehicular distribution in an inhomogeneous fashion using vehicle clusters that are distributed according to a Laplacian distribution around cluster center points is a simple way to increase model fidelity in medium congestion regions. Only for highly congested areas the vehicular distribution can be well approximated using a uniform distribution. Furthermore, our analysis of network simulator data shows that packet loss due to hidden node interference can be captured in a straight-forward manner that consists of a linear affine model combined with a Gamma distributed random variable. The results presented here hopefully help improve the accuracy of channel load models and the quality of analytical approaches to performance modeling.

References

[1] D. Krajzewicz, J. Erdmann, M. Behrisch, and L. Bieker, "Recent Development and Applications of SUMO – Simulation of Urban MObility," *Int. J. Adv. Syst. Meas.*, vol. 4, 2012.

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[2] T. Blazek, G. Ghiaasi, C. Backfrieder, G. Ostermayer, and C. Mecklenbräuker, "IEEE 802.11p Performance for Vehicle-to-Anything Connectivity in Urban Interference Channels," in *12th Eur. Conf. Antennas Propag.*, 2018, pp. 1–5.

[3] P. Muhlethaler, Y. Bouchaala, O. Shagdar, and N. Achir, "Evaluating the gain of directional antennas in linear vanets using stochastic geometry," in *2017 International Conference on Performance Evaluation and Modeling in Wired and Wireless Networks (PEMWN)*, Nov 2017, pp. 1–7.

[4] M. Ni, M. Hu, Z. Wang, and Z. Zhong, "Packet reception probability of vanets in urban intersecton scenario," in *2015 International Conference on Connected Vehicles and Expo (ICCVE)*, Oct 2015, pp. 124–125.

[5] M. J. Farooq, H. ElSawy, and M. Alouini, "Modeling inter-vehicle communication in multi-lane highways: A stochastic geometry approach," in *2015 IEEE 82nd Vehicular Technology Conference (VTC2015-Fall)*, Sept 2015, pp. 1–5.

[6] V. V. Chetlur and H. S. Dhillon, "Success probability and area spectral efficiency of a vanet modeled as a cox process," *IEEE Wireless Communications Letters*, pp. 1–4, 2018.

[7] T. Blazek and C. Mecklenbräuker, "Measurement-Based Burst-Error Performance Modeling for Cooperative Intelligent Transport Systems," *IEEE Trans. Intell. Transp. Syst.*, 2018.

[8] J. Gozalvez, M. Sepulcre, and R. Bauza, "Ieee 802.11p vehicle to infrastructure communications in urban environments," *IEEE Communications Magazine*, vol. 50, no. 5, pp. 176–183, May 2012.

[9] T. Blazek and C. F. Mecklenbräuker, "Complexity SNR-Based Packet Level Burst-Error Model for Vehicular Ad-Hoc Networks," in *IEEE VTC Fall 2018*. Chicago: IEEE, 2018, p. 5.

[10] F. Abrate, A. Vesco, and R. Scopigno, "An Analytical Packet Error Rate Model for WAVE Receivers," in *Veh. Technol. Conf. (VTC Fall), 2011 IEEE*, Sep 2011, pp. 1–5.

[11] OpenStreetMap contributors, "Planet dump retrieved from https://planet.osm.org ," https://www.openstreetmap.org , 2017.

[12] C. Sommer and F. Dressler, "Progressing Toward Realistic Mobility Models in VANET Simulations," *IEEE Communications Magazine*, vol. 46, no. 11, pp. 132–137, November 2008.

[13] Y. Zang, B. Walke, G. Hiertz, and C. Wietfeld, "IEEE 802.11p-based Packet Broadcast in Radio Channels with Hidden Stations and Congestion Control," Dec 2016.

[14] *Intelligent Transport Systems (ITS); Decentralized Congestion Control Mechanisms for Intelligent Transport Systems operating in the 5 GHz range; Access layer part*, European Telecommunications Standards Institute Std., Jul 2011.

[15] J. Karedal, N. Czink, A. Paier, F. Tufvesson, and A. F. Molisch, "Path Loss Modeling for Vehicle-to-Vehicle Communications," *Trans. Veh. Technol.*, vol. 60, no. 1, pp. 323–328, Jan 2011.

[16] S. Gräfling and M. Petri, "Performance Evaluation of IEEE 1609 WAVE and IEEE 802 . 11p for Vehicular Communications," pp. 344–348, 2010.

[17] M. Sepulcre, J. Gozalvez, B. Coll-Perales, M. C. Lucas-Estañ, and J. R. Gisbert, "Empirical performance models for v2v communications," in *2015 IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing*, Oct 2015, pp. 737–742.