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Empirical Performance Models for V2V Communications

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Abstract— **Vehicular networks will significantly enhance traffic safety and management thanks to the wireless exchange of messages between vehicles and between vehicles and infrastructure nodes. Vehicular networks will make use of the IEEE 802.11p technology in the 5.9GHz frequency band. Simulation studies are generally utilized to analyze the performance of vehicular communications and networking protocols. The impact of these studies can be significantly influenced by the accuracy of the employed models, in particular at the radio and physical level. In this context, this paper proposes a set of 48 computationally inexpensive empirical performance models for V2V (Vehicle-to-Vehicle) communications. The models have been derived from an extensive V2V measurement campaign, and model the PDR (Packet Delivery Ratio) and PSR (Packet Sensing Ratio) as a function of the distance between transmitter and receiver. The set of models include PDR and PSR curves for urban and highway environments considering three different transmission power levels and eight data rates (modulation and coding schemes). The proposed models can be easily integrated into communications and networking simulators.**

Keywords—connected vehicles; vehicular networks; empirical performance models; Vehicle-to-vehicle; V2V; packet delivery ratio; packet sensing ratio.

I. INTRODUCTION

Connected vehicles are a key component of the current automotive revolution and will be essential for the next generation of intelligent transportation systems [1]. Connected vehicles enable the dynamic exchange of information among vehicles (V2V, Vehicle-to-Vehicle), and among vehicles and infrastructure nodes (V2I, Vehicle-to-Infrastructure) using wireless communications. The information exchange is based on the periodic transmission and reception of 1-hop broadcast packets on the so called control channel, using the IEEE 802.11p technology in the 5.9GHz frequency band. Each packet includes positioning and basic status information of the transmitting vehicle that is utilized by higher layer protocols and vehicular applications. For example, safety applications exploit the position and speed information of nearby vehicles to detect potential road dangers with sufficient time for the driver to react.

Simulation studies are generally used to analyze the benefits of vehicular applications, and evaluate the performance of vehicular communication and networking protocols. These studies employ different types of simulators, including some specifically developed for vehicular environments such as iTETRIS [2] or Veins [3]. The validity of the conclusions obtained using simulations notably depend on the accuracy of physical layer and radio propagation models [4]. Accurate models can be very complex and computationally expensive. To find a balance between realistic modeling and tractability, this paper proposes a set of 48 computationally inexpensive empirical performance models for V2V communications. The set of proposed models can be easily used in vehicular simulations, and have been derived from an extensive V2V measurement campaign. They model the PDR (Packet Delivery Ratio) and PSR (Packet Sensing Ratio) as a function of the distance between transmitter and receiver. The PDR can be defined as the probability of correctly receiving a packet, and the PSR as the probability of sensing a packet (which might or might not be correctly received). PDR and PSR models have been obtained for urban and highway environments considering 3 different transmission powers and 8 data rates (modulation and coding schemes). While the PDR models can be used to derive other performance metrics, the PSR models can be exploited to estimate channel load levels. Controlling channel load levels (e.g. using congestion and awareness control protocols [5]) is of paramount relevance to ensure the stability of vehicular networks and satisfy the application requirements. To the authors' knowledge, this is one of the first studies deriving PSR models from experimental data. The proposed models can be easily integrated into communications and networking simulators. Detailed information about how to use the proposed models is provided in section V.

II. RELATED WORK

Several IEEE 802.11p measurement campaigns have been reported in the literature. The general aim of these studies is to assess the IEEE 802.11p communications performance under different conditions. For example, the work in [6] presents the results of an extensive measurement campaign conducted to investigate the impact of operating and propagation conditions on IEEE 802.11p V2I communications. The objective of the measurement campaign was to define a set of RSU (Road Side Unit) deployment guidelines to assist stakeholders in their deployment. Boban et al. analyze in [7] the efficiency of V2V and V2I communications for cooperative awareness in urban, suburban, and highway environments. To this aim, they exploit

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the data obtained in four different test sites within the scope of the DRIVE-C2X project. Based on this data, they compute different awareness metrics, such as the neighborhood awareness ratio or the ratio of neighbors above range. These studies show the relevance of empirically testing the performance of IEEE 802.11p communications under real conditions, although they did not derive performance models from the obtained data. Some studies go one step further and derive performance models from the measured data. The work in [8] proposes a V2I packet error rate model based on Gilbert's model (previously proposed to model bit error bursts in packet switched networks) to statistically describe the packet error patterns observed in an extensive measurement campaign conducted within the ROADSAFE project. This model was extended in [9] to take into account specific street layouts and propagation impairments. For V2V communications, the work in [10] proposes a model for packet loses and latency based on empirical data. The model takes into account speed and distance between vehicles. The packet loss model is based on the concept of profiles, where a profile represents a single uninterrupted wireless connection between two vehicles. The latency model is simpler and takes into account the statistical distribution of the latency values in the empirical data. The work in [11] characterizes for V2V scenarios the PIR (Packet Inter Reception) time distribution and its relationship with PDR, speed and distance between vehicles based on empirical data. To this aim, the authors employ the Gilbert-Elliot model.

The studies reviewed show the importance of using computationally inexpensive performance models in vehicular communications and networking simulation studies, although they present certain limitations. First, they are normally designed for a fixed set of transmission parameters, and therefore cannot be used to e.g. identify the minimum transmission power needed to satisfy certain application requirements. Second, they are only valid for a single environment (e.g. urban), and cannot be used to corroborate the validity of a protocol in different environments. Third and last, they normally focus only on PDR levels or similar metrics, but do not model metrics related to the channel load generated, which is also critical for vehicular networks. The empirical models proposed in this paper overcome all these limitations by including highly tractable PDR and PSR models for 3 different transmission powers and 8 data rates for urban and highway environments.

III. Methodology

A. Measurement campaign

The measurement campaign was conducted near the city of Elche (Spain). The urban measurements were conducted in Mariano Benlliure street, a single-lane straight street in the city center with parked cars at both sides; the street is more than 800m long (see Fig. 1). The highway-like measurements were conducted in one of the industrial areas of Elche, in a two-lane straight street without parked cars or buildings (see Fig. 2), and that is more than 1km long.

The measurement campaign was conducted using two OBUs (On Board Units), each of them equipped with an IEEE 802.11p DENSO WSU (Wireless Safety Unit) prototype and mounted on a standard vehicle. Each OBU used a single Nippon omni-directional antenna with 0dBi gain, placed on the roof of a vehicle and connected to the DENSO WSU prototype with an LMR240 antenna cable of 3m length and approximately 3dB cable loss. Each OBU employed a Novatel SMART-V1-2US-PVT GPS receiver to accurately track each vehicle's position. This receiver presents a reference positioning accuracy of 1.8m (RMS) and 20Hz maximum update rate.

Fig. 1. Picture of Mariano Benlliure street (Elche, Spain) where the measurement campaign for the urban environment was conducted.

Fig. 2. Street on the industrial area of Elche, Spain, where the measurement campaign for the highway-like environment was conducted.

The measurement campaign was conducted to derive the PDR and PSR models for 48 experiments: 3 transmission power levels (P_t=10, 15 and 20dBm), 8 data rates (*DR*=3, 4.5, 6, 9, 12, 18, 24 and 27 Mbps) and 2 environments (urban and highway). Multiple test-drives were conducted for each experiment. In each test-drive, the transmitting OBU moved away while the other one was static. In all the experiments, the static OBU was located to have LOS (Line-of-Sight) conditions between transmitting and receiving antennas. To derive the PDR models, only the packet ID of all correctly received packets and the distance between transmitter and receiver were needed. However, to derive the PSR models, the CBR (Channel Busy Ratio) experienced by the receiving OBU was also logged. The CBR is defined as the percentage of time that the channel is sensed as busy, and was needed because the radio interface does not log sensed packets. In the proposed scenario, the CBR experienced by the receiver is maximum at short distances to the transmitter because all packets are sensed. As the transmitting OBU moves away, the CBR experienced by the receiver decreases because the probability of sensing the packets transmitted decreases with the distance. The PSR can be derived by normalizing the CBR values by the CBR experienced at short distances where all packets are sensed. Since the DENSO WSU device logs the CBR in integer units, the packet transmission frequency was set to a high value (500Hz). The use of a high packet transmission frequency allowed measuring the CBR without significant resolution loses. Please note that there were no packet collisions because there was only one transmitting vehicle. The most important configuration parameters used in the experiments are summarized in Table I.

TABLE I. CONFIGURATION PARAMETERS

Parameter	**Value**
Transmission power [dBm]	10, 15, 20
Beacon transmission frequency [Hz]	500
Data rate [Mbps]	3, 4.5, 6, 9, 12, 18, 24, 27
Antenna gain [dBi]	0
Channel frequency [GHz]	5.9
Packet size [Bytes]	250

B. Mathematical models

The proposed models are based on mathematical functions to maximize their tractability. There are several mathematical functions that can be used to model the PDR and PSR which have a symmetric *S* shape. These functions can be grouped into three broad categories: exponential, piecewise-defined, and sigmoid functions [12]. A function from each of these categories has been selected to identify the one that best fits the measured data. More complex functions can also provide good fits, but the selected functions provide a reasonable trade-off between accuracy and analytical-simulation tractability. The functions selected are presented in Table II, where d represents the distance between transmitter and receiver in meters, and A is the upper asymptote or maximum value (A=1 to model PDR and PSR curves). Fitting parameters p_1 and p_2 modify the characteristics of the *S*-shaped functions, such as the distance at which the PDR or PSR curve starts decreasing, or the slope of the curve.

TABLE II. FUNCTIONS SELECTED FOR PERFORMANCE MODELING

Name	**Equation**
Exponential	$f_{\exp}(d) = A \cdot e^{-(p_1 \cdot d)^{p_2}}$
Piecewise	$f_{pie}(d) = \begin{cases} A & d < p_1 \\ k \cdot \left(\frac{1}{d} - \frac{1}{p_2}\right) & p_1 \le d < p_2 \\ 0 & d \ge p_2 \end{cases}$ where $k = A / (1/p_1 - 1/p_2)$
Sigmoid	$f_{sig}(d) = A \cdot \left[1 - \frac{1}{1+e^{-p_1(d-p_2)}}\right]$

A curve fitting process has been performed to derive the p_1 and p_2 parameters that minimize the root-mean-square error (RMSE). The RMSE represents the sample standard deviation of the differences between the measured data and the proposed modeling functions. It can be calculated with the following equation:

$$RMSE_j = \sqrt{\frac{\sum_d \left(f_j(d) - g(d)\right)^2}{M}} \quad (1)$$

where $f_j(d)$ represents the modeling functions (j {exp,pie,sig}), $g(d)$ represents the measured data and M the number of data samples.

IV. RESULTS

A. Data processing

The data obtained in the measurement campaign needs to be processed to derive the PDR and PSR models. Fig. 3a shows the PDR curves obtained in 4 consecutive test-drives in the urban environment considering P_t=15dBm and 6Mbps data rate. Each PDR level was calculated as the ratio between the number of packets correctly received and the total number of packets transmitted. As it can be observed, the PDR can become especially unstable for medium and high distances in this environment. The average PDR of the 4 test-drives (shown in Fig. 3b) is used as input for the curve fitting process to derive the model, i.e. the p_1 and p_2 parameters that minimize the RMSE. As an example, Fig. 3b also shows the sigmoid function that best fits the experimental data for P_t=15dBm and 6Mbps.

A similar process was used to obtain the PSR models. The main difference is that the PSR curves were derived from the CBR levels measured. Fig. 4a shows the CBR levels measured in the same 4 consecutive drive-tests of Fig. 3 (i.e. P_t=15dBm and 6Mbps data rate). From these curves, the average CBR curve was calculated and used as input for the curve fitting process. The curve fitting process identifies the parameters of the model to fit the CBR empirical curve. The PSR model is then obtained by normalizing the CBR model by its maximum value. Fig. 4b depicts the average CBR values once they were normalized, and the PSR models considering the functions proposed (exponential, piecewise and sigmoid).

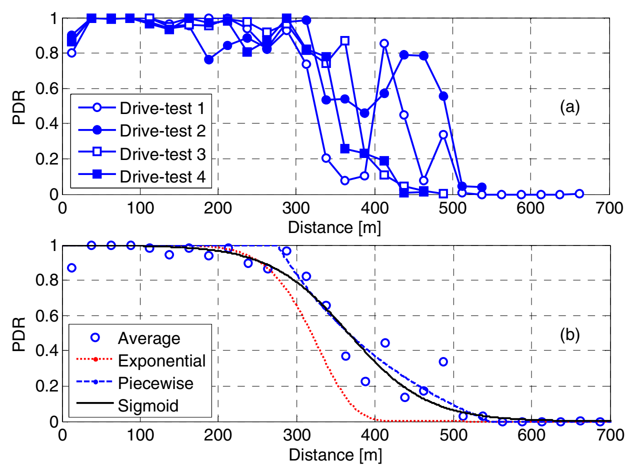

Fig. 3. PDR curves (a) obtained in 4 drive-tests and (b) obtained by averaging the 4 drive-tests and adjusting the proposed functions. Parameters: P_t=15dBm, data rate = 6Mbps. Urban environment.

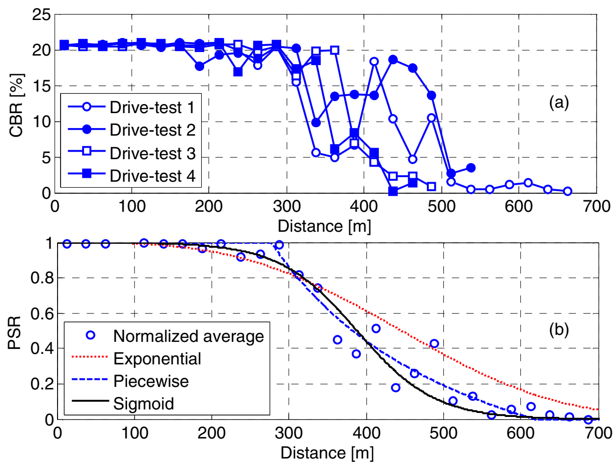

Fig. 4. (a) CBR curves obtained in 4 test-drives and (b) PSR curves obtained by averaging and normalizing the 4 test-drives and adjusting the proposed functions. Parameters: P_t=15dBm, data rate = 6Mbps. Urban environment.

B. Mathematical model selection

The curve fitting process was performed for all the experiments conducted and the 3 mathematical functions selected. To have a homogeneous set of models, the objective was to identify the mathematical function that minimizes the RMSE considering the whole set of experiments. Table III shows the average RMSE obtained considering all the experiments for urban and highway scenarios and differentiating RMSE values for PDR and PSR models. As it can be observed, the sigmoid function minimizes the average RMSE. In fact, when comparing the RMSE obtained with the 3 mathematical functions in each experiment, the sigmoid function produced the minimum value in the majority of experiments (see Table IV). The sigmoid function has been then selected to model the PDR and PSR curves from the measured data.

TABLE III. AVERAGE RMSE FOR ALL EXPERIMENTS

Environment	Model	Exp	Pie	Sig
Urban	PDR	0.071	0.064	0.054
	PSR	0.085	0.08	0.072
Highway	PDR	0.120	0.094	0.075
	PSR	0.122	0.104	0.071

TABLE IV. PERCENTAGE OF EXPERIMENTS WHERE EACH MATHEMATICAL FUNCTION PRODUCED THE MINIMUM RMSE

Environment	Model	Exp	Pie	Sig
Urban	PDR	28%	16%	56%
	PSR	38%	24%	38%
Highway	PDR	28%	6%	66%
	PSR	16%	12%	72%

C. PDR and PSR models

Table V and Table VI present the complete set of PDR and PSR models derived from the measurement campaign conducted. Based on the sigmoid function, the p_1 and p_2 parameters can be employed to easily plot and use the proposed models for 3 different transmission power levels and all IEEE 802.11p data rates. As an example, Fig. 5 depicts the PDR models derived for the highway environment for P_t=20dBm and all possible data rates. As it can be observed, the use of high data rates can notably reduce the communications range. In fact, while high PDR levels can be experienced up to around 500m for low data rates, the use of the highest data rates reduces this distance to around 100m. Fig. 6 shows the effect of increasing the transmission power for a fixed data rate (6Mbps). The results obtained show that increasing the transmission power by 5dB augments the distance at which a PDR of 0.8 is obtained by approximately 130m.

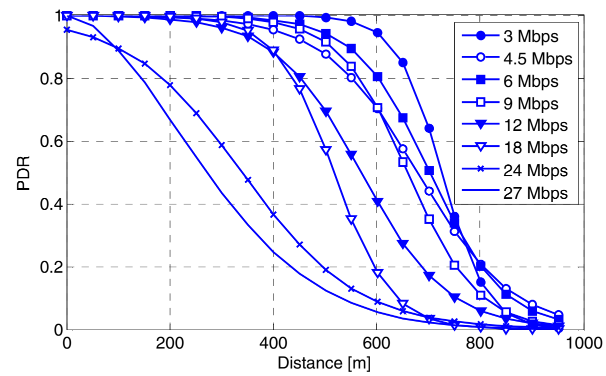

Fig. 5. PDR models derived for the highway environment and P_t=20dBm.

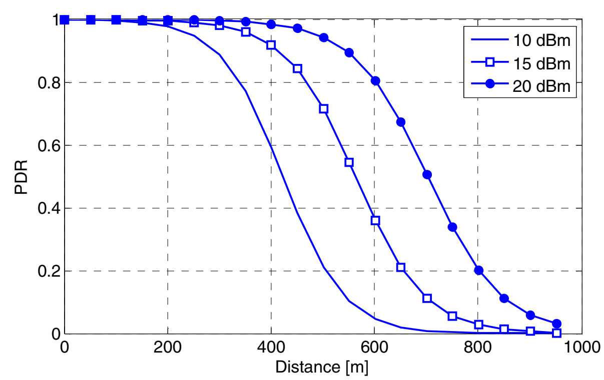

Fig. 6. PDR models derived for the highway environment and 6Mbps.

Fig. 7 plots the PDR and PSR models derived for a transmission power of 20dBm in the highway environment for the maximum and minimum data rates. The results obtained show that the difference between the PDR and PSR models can be very small for low data rates. This is the case because low data rates employ robust modulation and coding schemes and nearly all sensed packets were correctly decoded. However, for high data rates, the difference between the PDR and PSR curves is relevant. The use of less robust modulation and coding schemes results in that a lower number of sensed packets could be correctly decoded.

TABLE V. PDR AND PSR MODELS FOR THE URBAN ENVIRONMENT

Data rate	Tx. Power (dBm)	PDR		PSR	
		p1	p2	p1	p2
3	10	0.021	270	0.021	274
	15	0.025	369	0.024	373
	20	0.005	607	0.005	624
4.5	10	0.011	351	0.009	394
	15	0.006	467	0.006	508
	20	0.008	446	0.008	465
6	10	0.015	269	0.012	310
	15	0.019	367	0.016	391
	20	0.007	591	0.008	670
9	10	0.025	182	0.023	234
	15	0.016	357	0.009	459
	20	0.014	382	0.009	453
12	10	0.032	154	0.049	203
	15	0.02	230	0.017	316
	20	0.014	361	0.008	548
18	10	0.029	145	0.031	233
	15	0.02	197	0.023	308
	20	0.021	256	0.007	390
24	10	0.042	99	0.026	185
	15	0.042	137	0.036	225
	20	0.035	182	0.019	263
27	10	0.046	95	0.1	224
	15	0.026	140	0.1	497
	20	0.03	156	0.036	243

TABLE VI. PDR AND PSR MODELS FOR THE HIGHWAY ENVIRONMENT

Data rate	Tx. power	PDR		PSR	
		p1	p2	p1	p2
3	10	0.028	538	0.028	542
	15	0.02	631	0.02	645
	20	0.023	726	0.023	738
4.5	10	0.014	448	0.07	502
	15	0.012	557	0.013	648
	20	0.011	679	0.009	774
6	10	0.017	423	0.022	460
	15	0.015	563	0.014	633
	20	0.014	703	0.011	773
9	10	0.011	388	0.022	463
	15	0.029	585	0.018	652
	20	0.015	660	0.019	737
12	10	0.01	277	0.022	397
	15	0.022	443	0.019	481
	20	0.012	570	0.016	721
18	10	0.011	173	0.011	369
	15	0.012	365	0.012	482
	20	0.018	517	0.011	642
24	10	0.037	96	0.015	242
	15	0.01	192	0.026	395
	20	0.009	340	0.017	478
27	10	0.042	85	0.013	195
	15	0.011	160	0.018	402
	20	0.009	281	0.017	462

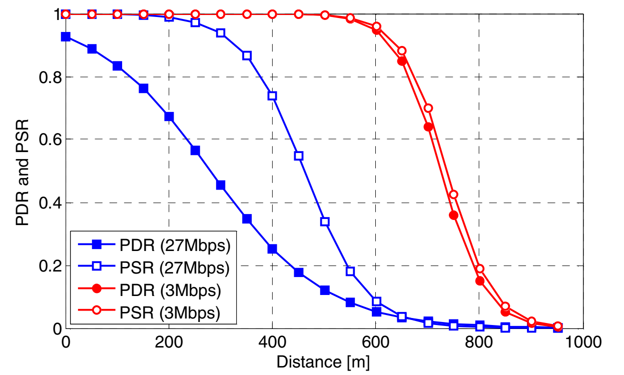

Fig. 7. PDR and PSR models for P_t=20dBm in the highway environment considering the maximum and minimum data rates.

V. USING THE PDR AND PSR MODELS

The proposed models are characterized by a low computational complexity and high tractability, and can hence be used for many different purposes. The PDR models can be used to derive different performance metrics in order to evaluate the capability of 1-hop broadcast transmissions to satisfy the vehicular application requirements. For example, the PDR models can be exploited to identify the RCR (Reliable Connectivity Range), defined as the distance up to which the experienced PDR is above certain threshold [6]. The RCR represents the range up to which high quality V2V communications can be established. Other metrics such as the average packet inter-reception time can also be estimated. The average packet inter-reception time can be estimated as the inverse of the PDR models provided:

$$PIR(d) = \frac{1}{PDR(d)} \tag{2}$$

Similarly, the probability of receiving at least one packet in certain time window p can also be estimated from the PDR models proposed. Considering that n packets are transmitted within the time window by a vehicle at a constant distance d and that packet receptions are independent, this probability can be estimated as:

$$p(d) = 1 - (1 - PDR(d))^n \tag{3}$$

The PSR models can be used to estimate the channel load generated by a vehicle. This can be useful to estimate the set of transmission parameters that minimize the channel load generated by a vehicle. To this aim, the PSR can be used to calculate the channel occupancy footprint (or footprint in short), defined as the total channel resources consumed by the radio of a vehicle in both time and space dimensions [13]. The footprint can be calculated as the spatial integral of the channel load contribution of the vehicle. This contribution is equal to the packet transmission frequency, F, multiplied by the packet duration, T, and the PSR. As a result, the footprint of a vehicle can be expressed as:

$$footprint = \int_d load(d) = F \cdot T \cdot \int_d PSR(d) \tag{4}$$

The PSR models can also be used to estimate the channel load experienced by a vehicle as a result of packet transmissions from other vehicles. In particular, the CBR experienced by a vehicle can be estimated as the addition of the load contribution of all its neighboring vehicles:

$$C\hat{B}R = \sum_{i \in \Psi} F_i \cdot T_i \cdot PSR(d_i) \tag{5}$$

where Ψ represents the set of neighboring vehicles, F_i represents the packet transmission frequency of neighbor vehicle i, T_i represents its packet duration, and d_i its distance to the vehicle for which the CBR is estimated. The CBR estimated with equation (5) is an upper bound of the actual CBR since it does not take into account packet collisions. This is the case because when packets collide and overlap in time, the amount of time the channel is sensed as busy is reduced compared to this upper bound.

Since the models include different transmission power levels, they can also be exploited to estimate the minimum power needed to satisfy certain application requirements, e.g. the minimum power needed to reach certain RCR. Any simulation study using the proposed models will have the opportunity to corroborate the results obtained in two different environments (urban and highway).

VI. Conclusions

This paper proposes a set of 48 computationally inexpensive empirical performance models for V2V communications that can be easily used for vehicular simulation studies. Derived from an extensive V2V measurement campaign, they model the PDR and PSR between transmitter and receiver for 3 different transmission powers and 8 data rates, and considering urban and highway scenarios. The proposed models can be easily integrated into communications and networking simulators.

References

[1] N. Lu et al., "Connected Vehicles: Solutions and Challenges", *IEEE Internet of Things Journal*, vol. 1, no. 4, pp. 289-299, Aug. 2014.

[2] M. Rondinone et al., "iTETRIS: a modular simulation platform for the large scale evaluation of cooperative ITS applications" *Simulation Modelling Practice and Theory*, vol. 34, pp. 99-125, May 2013.

[3] C. Sommer et al., "Bidirectionally Coupled Network and Road Traffic Simulation for Improved IVC Analysis", *IEEE Transactions on Mobile Computing*, vol. 10 (1), pp. 3-15, January 2011.

[4] J. Gozalvez et al., "Impact of the Radio Channel Modelling on the Performance of VANET Communication Protocols", *Telecommunication Systems*, vol. 50 (3), pp. 149-167, July 2012.

[5] M. Sepulcre et al., "Congestion and Awareness Control in Cooperative Vehicular Systems", *Proceedings of the IEEE*, vol. 99 (7), pp. 1260-1279, July 2011.

[6] 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.

[7] M. Boban et al., "Measurement-based Evaluation of Cooperative Awareness for V2V and V2I Communication", *Proc. IEEE Vehicular Networking Conference (VNC)*, Paderborn (Germany), 3-5 Dec. 2014.

[8] V. Shivaldova et al., "Vehicular Link Performance: From Real-World Experiments to Reliability Models and Performance Analysis", *IEEE Vehicular Technology Magazine*, vol. 8, no. 4, pp. 35–44, 2013.

[9] V. Shivaldova et al., "A Model for Vehicle-to-Infrastructure Communications in Urban Environments", *Proc. IEEE ICC Workshop on Dependable Vehicular Communications (DVC)*, London (United Kingdom), 12 June 2015.

[10] S. Demmel et al., "An IEEE 802.11p empirical performance model for Cooperative Systems applications", *Proc. Int. IEEE Conference on Intelligent Transportation Systems (ITSC)*, The Hague, (The Netherlands), pp. 590-596, 6-9 Oct. 2013.

[11] F. Martelli et al., "A measurement-based study of beaconing performance in IEEE 802.11p vehicular networks", *Proc. IEEE International Conference on Computer Communications (INFOCOM)*, Orlando (USA), pp. 1503-1511, 25-30 March 2012.

[12] B. Coll-Perales et al., "Empirical Performance Models for P2P and Two Hops Multi-hop Cellular Networks with Mobile Relays", *Proc. ACM Workshop on Performance Monitoring, Measurements and Evaluation of Heterogeneous Wireless and Wired Networks (PM2HW2N)*, Barcelona, Spain, 3-8 Nov. 2013.

[13] Qi Chen et al., "Mathematical Modeling of Channel Load in Vehicle Safety Communications", *IEEE Vehicular Technology Conference VTC-Fall*, pp.1-5, 5-8 Sept. 2011.