On the Impact of Traffic Models on Inter-vehicular Broadcast Communications

Roberta Fracchia, Michela Meo, Dario Rossi
Politecnico di Torino – Italy
firstname.lastname@polito.it

Abstract

This paper focuses on the study of vehicle-to-vehicle broadcast communications, investigating the impact of different traffic-flow models on the achievable performance from a networking perspective. After introducing and comparing a few popular microscopic models, representing single-lane highway traffic, we inspect their impact on both i) the network connectivity and ii) the performance of a simple position-based broadcast algorithm, which assumes that an estimate of the neighborhood position information is available by means of a beaconing procedure performed at the routing layer. By simulation, we show that the specific traffic model only marginally affects the network connectivity, whereas the peculiar dynamic of the vehicular traffic may have a very deep impact on beaconing and position estimation based approaches.

I. Introduction

A promising field in wireless communications, that recently attracted much attention from the research community, is the so-called ad hoc vehicle-to-vehicle communication. On the one hand, inter-vehicular network research is fueled by the appeal of an entirely new market segment – i.e., geographically-contextualized advertisement, entertainment applications and services aimed at improving passengers traveling comfort, such as traffic-related information delivery to vehicles' drivers. On the other hand, the enormous human and social costs of road deaths and injuries is pushing governments and companies to invest on the deployment of new applications for road safety, based on wireless technologies for inter-vehicle communication [1]. Indeed, the price paid for mobility in Europe, in the year 2000, accounted for over 40,000 deaths and more than 1.7 million injuries [2]: in this context, a "killer application" would paradoxically be the one that actually helped in saving many human lives.

Even if wireless technology is now mature enough to allow for the deployment of such services, inter-vehicular ad hoc networking still poses a number of challenges [3]. Indeed, there are several aspects that differentiate vehicle-to-vehicle communication from other ad hoc networks. Two of these aspects are particularly significant. The first peculiarity concerns vehicles mobility. On the one hand, given the geometrical constraint represented by the road, vehicle movements are predictable to some extent and can be exploited to improve networking protocols. On the other hand, vehicles mobility makes the network topology prone to fragmentation, and connectivity highly variable. The second peculiarity is that, for many services, communication is needed only between vehicles that are geographically close to each other. In these cases, in contrast to traditional networks, the information has to be targeted to unknown receivers in certain geographic regions: thus, nodes can be addressed through their approximate location rather than being individually identified.

Geographical services can be implemented through broadcasting algorithms, whose effectiveness is strongly affected by the network topology and connectivity, which, in their turn, depend on the mobility model. Thus, when benchmarking any broadcast algorithm to be used for inter-vehicle communication, realistic and accurate mobility models are a must. In this context, the objective of this paper is to assess the impact of the vehicular traffic models on the communication performance: we select a set of popular traffic models, representing single-lane highway scenarios, and we analyze their behavior from a networking perspective. We first compare these models in terms of both traffic-related metrics and the network connectivity. Then, we focus on their impact on the communication performance of a very simple algorithm representative of the position-based broadcast algorithm class: the approach we adopt is, in a sense, complementary to the one in [4], where several broadcast schemes are compared under the same mobility model. We observe that, despite differences in the vehicular traffic dynamics, network connectivity remains largely unaffected by the specific used model. On the contrary, the traffic model plays a critical role in determining the communication performance of position-based broadcast schemes; moreover, we believe that these differences are likely to be even more pronounced when more complex road topologies and vehicular traffic dynamics (e.g, with multiple lanes, intersections, on- and off-ramps, etc.) come into play.

II. Related Work

Vehicular traffic modeling is now older than seven decades and several attempts have been undertaken to understand how the traffic flows. Traffic can be *macroscopically* described as a flow: i.e., considering a pipe-tubes system, traffic is intended as the fluidic amount of vehicles that are traveling in a given direction at a given speed. While this kind of abstraction allows to describe aspects such as the level of congestion of single roads, it is not suited to model neither the behavior of single vehicles, nor their interaction. To our purpose instead, it is essential to describe the traffic at a *microscopic* level, trying to abstract real drivers behavior in a few mathematical rules. Two classes of models currently in use, namely Cellular Automata (CA) and Coupled Maps (CM), display properties similar to the real traffic dynamics at a microscopic level. Already introduced in the 1950s, these microscopic modeling techniques have been increasingly used in the last decade [5], [6], [7], [8], [9], also because of the good match they exhibit with empirical traffic measurements [10], [11].

Although such models have been analyzed in depth for what concerns the vehicular traffic properties, the properties of the communication between vehicles have not been the object of an exhaustive investigation yet. Besides, only a few performance studies do exist that make use of realistic traffic models. Among these works, we may cite [12], which studies the connectivity of a network of vehicles moving according to [5], and [3], [13], [14], that use different commercial microscopic traffic simulators: [3], [13] investigate the connection lifetime and other path properties, whereas [14] focuses on the impact of the traffic density on the delay.

However, the networking community should be aware that no universally accepted mobility model has emerged yet, whereas several traffic models do exist, each of which is capable of capturing some of the several different aspects of the complex vehicular movement. Therefore, in our view, it is important to gather a deeper understanding of the impact that the choice of a peculiar traffic model can have on the performance of any communication algorithm: to the best of our knowledge, this is the first work that takes a step toward this direction.

III. Single-lane traffic models

In microscopic modeling each *vehicle* is individually resolved: a vector of state variables (x, v) describes the spatial location and the speed of the vehicle along a one-dimensional road. A *model* then consists of a set of rules or equations to update the state vector over time, depending on the states of other vehicles around. In the following we describe a few of the most popular traffic models, chosen within the Cellular Automata (CA) and Coupled Maps (CM) classes.

A. Discrete-Space and Discrete-Time Models (CA)

CA models are discrete in both space and time, which is an advantage for computer simulation. Time can be measured in "steps", space in "cells" of length l, representing the space that a car occupies in a jam, and speed in "cells per step"; usually these units are implicitly assumed and left out of the equations. Moreover, the *gap* among two consecutive cars is defined and used to specify the rules that mimic the actual driver's behavior: by denoting with $\tilde{x}$ the position of the car ahead, the gap can be defined as the bumper-to-bumper distance minus the cell length $g = \tilde{x} - x - l$. Finally, the road is wrapped around, so that a vehicle leaving the last cell enters the first one.

Nagel and Schreckenberg (NaSch): Let us first introduce the Nagel and Schreckenberg (NaSch) automaton [5], which is a minimal model, in the sense that any simplification would lead to a loss of realism; its set of rules is on the left hand-side of Figure 1. Update rules are performed in parallel: a first loop over all cars determines new vehicular speeds; then, a second loop updates vehicles positions. The first two rules describe deterministic car-following behavior: drivers try to accelerate by one speed unit except when the maximum speed v_{max} is reached or when the gap from the vehicle ahead is too small. The third rule introduces random noise: with probability P_{noise} (typically set to 0.16) a vehicle ends up being slower than what deterministically calculated; this parameter simultaneously models i) speed fluctuations at free driving, ii) over-reactions at braking and car-following, and iii) randomness during acceleration periods. The model implicitly introduces a reaction time of the order of the timestep: rather than representing the actual driver's reaction time, which would be much shorter, the reaction time is a measure of the time elapsed between the stimulus and the action of the vehicle.

$$
\begin{cases}
\textbf{NaSch Rules} \\
\quad v \leftarrow \min\{v+1, v_{max}\} \\
\quad v \leftarrow \min\{v, g\} \\
\quad v \leftarrow \max\{v-1, 0\} \\
\qquad \text{w.p. } P_{noise} \\
\textbf{Motion-update} \\
\quad x \leftarrow x + v
\end{cases}
\begin{cases}
\textbf{Toca Rules} \\
\quad \text{if}(g > v\tau_H),\ \text{w.p. } P_{ac} \\
\qquad v \leftarrow \min\{v+1, v_{max}\} \\
\quad v \leftarrow \min\{v, g\} \\
\quad \text{if}(g < v\tau_H),\ \text{w.p. } P_{dc} \\
\qquad v \leftarrow \max\{v-1, 0\} \\
\textbf{Motion-update} \\
\quad x \leftarrow x + v
\end{cases}
\begin{cases}
\textbf{CM Rules} \\
\quad v_{safe} = v + \frac{g-v}{\overline{v}/b} \\
\quad v_{des} = min\{v+a, v_{safe}, v_{max}\} \\
\textbf{Velocity-update} \\
\quad v = max\{0, v_{des} - a\epsilon\} \\
\textbf{Motion-update} \\
\quad x \leftarrow x + v
\end{cases}
$$

Fig. 1. Rules of CA and CM traffic models: NaSch (left), TOCA (center) and CM (right)

Velocity-Dependant Randomization (*VDR*): A simple modification to the previous set of rules due to Barlovic et al. [6] aims at taking into account more realistic driver behavior. Specifically, the model introduces a velocity-dependent randomization (VDR) rule, which means that P_{noise} depends on the vehicle speed at the beginning of the time step, and typically increases with speed. By denoting the noise with $P_{vdr}(v)$, we select $P_{vdr}(v) = 2/3P_{noise}$ for $v \leq v_{max}/2$ and $P_{vdr}(v) = 4/3P_{noise}$ for $v > v_{max}/2$, where P_{noise} is the value chosen for the NaSch model.

Time Oriented CA (*TOCA*): The Time Oriented CA (TOCA) due to Brilon and Wu [7] aims at introducing a higher amount of elasticity in the car following – that is, vehicles should accelerate and decelerate at larger distance to the vehicle ahead, and resort to emergency braking only if they get too close. For the TOCA velocity update operations are reported in the center of Figure 1. The first rule corresponds to the vehicle trying to accelerate, the second rule to the vehicle slowing down. The typical values for the free parameters are $(P_{ac}, P_{dc}, \tau_H) = (0.9, 0.9, 1.1)$.

B. Continuous-Space and Discrete-Time Models (CM)

Another important class of traffic models is represented by the so-called Coupled Maps: these models retain the advantage of being coarse-grained discrete in time, while space is continue: from a practical point of view, they are numerically as efficient as CA models, while offering the advantage of being easier to calibrate. The most popular model falling in this class is due to Gipps [8] but, in reason of its simpler notation, we report the formulation of Krauß's [9]. In this case, the velocity is limited not only by the maximum velocity v_{max}, but also by the desired acceleration a and by a safe velocity bound v_{safe}, which depends on the local conditions of the traffic; finally, the speed is subject to a random perturbation. In the model description, reported on the right hand-side of Figure 1, we denote by a the maximum vehicle acceleration and by b the maximum deceleration; denoting by $\tilde{v}$ the velocity of the car ahead at time t, we further indicate with $\overline{v} = (v + \tilde{v})/2$ the average of the vehicles velocities used to determine the safe speed bound. The parameters are set to $(a, b) = (0.2, 0.6)$, values that are standardly used in the literature, and ϵ is a random number in $[0, 1]$.

IV. TRAFFIC PROPERTIES AND NETWORK CONNECTIVITY

Despite the traffic models introduced in the previous section describe the same highway scenario, and thus represent similar vehicular dynamics, nevertheless some differences arise. In this section, we present typical traffic properties, related to vehicles distance and speed, that enlighten such differences and are further instrumental to a better understanding of the connectivity of the inter-vehicular networks.

The results reported in this section are obtained with a discrete event simulator that features a μs time-granularity, which is apt to describe networking dynamics, even though vehicle movements have a rather coarse time-scale. We consider a road of 8 km and we set the cell size to $l = 7.5$ m, the timestep to $t = 1.2$ s and the maximum speed to $v_{max} = 5$ cells/timestep (corresponding to 112 km/h), values that are commonly used in the literature. Results reported in the following are obtained with a confidence level of 99% and a confidence interval of 2%.

Figure 2 contrasts the typical measurement of traffic flow of the CA and CM models early described, i.e., the so-called *fundamental diagram*. The fundamental diagram depicts the traffic flow q (left hand-side plot) expressed in vehicles per hour, and the average vehicle velocity (right hand-side plot) as a function of the density ρ in vehicles per kilometer. Intuitively, there is no flow when there is no car on the road, thus $q = 0$, and there is

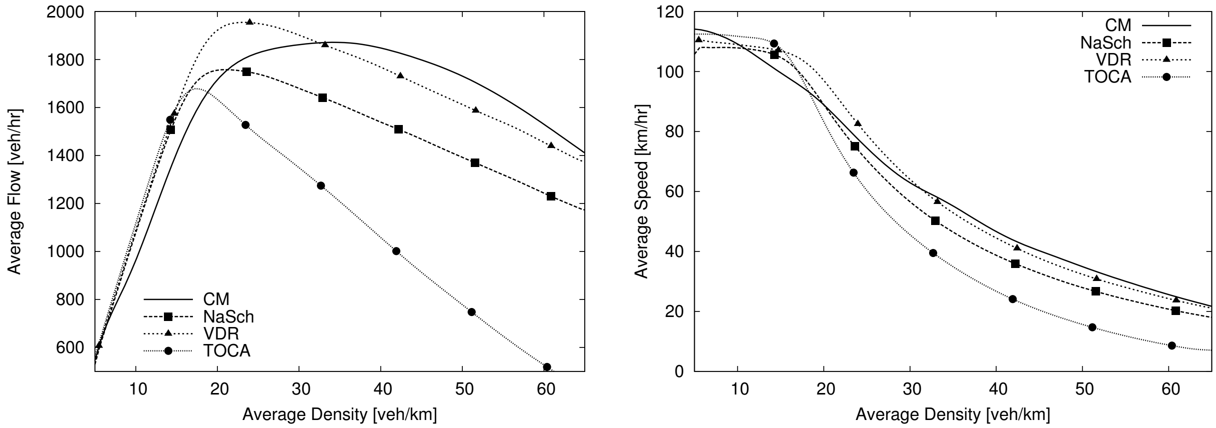

Fig. 2. Fundamental diagram of CA and CM traffic models: average flow (left) and speed (right) versus the vehicles density

also no flow when there is a dense jam $\rho = \rho_{max}$. In between, the flow trend is strictly related to the average vehicle velocity. Indeed, the flow reaches a maximum value q_{max} at some critical density ρ_c around 20 veh/km: below ρ_c, vehicles are in "free-flow" state (i.e., they move nearly at maximum speed without interference from each other); as density increases above ρ_c the velocity decreases, flow and density are strongly correlated and the system eventually becomes "jammed" (i.e., a state characterized by small speeds, small flows and large densities). Figure 2 shows that, although all the models reproduce the typical shape of the fundamental diagram, however some discrepancies arise: these are due the different behavioral rules adopted to mimic drivers' reaction to the external traffic conditions. Also, the transition between states is evident in both the flow as well as the velocity curves, though the actual slopes differ from model to model. In particular, the most significant differences, both in terms of speed and flow, appear in the congested states. Indeed, it is well known that, with an appropriate tuning of the models' parameter, the free-flow branch of *empirical* fundamental diagrams can be reproduced quite well, i.e., both the slope as well as the maximum are in agreement with empirical findings [10], [11]. Conversely, more significant differences between models and reality arise at higher vehicular densities, where the inter-model differences due to the specific driver behavioral rules are more pronounced: indeed, each model captures different aspects of the complex vehicular movement and no universally accepted model, capable of embedding them all, has emerged yet.

Since at high densities average speed differs from model to model, in Figure 3 we better investigate differences between models. Left-hand side plot of Figure 3 depicts the CDF obtained with these traffic models at the density $\rho = 45$ veh/km, that is above the critical threshold ρ_c. For this density, the CA models likely generate jams with *still* cars, while the CM model, given to its speed-continuity, allows a much finer discrimination of slowly-moving cars (crossover occurs around the 70^{th} percentile for speed around 60 km/hr). Right-hand side plot of Figure 3 shows how the speed changes during a small interval of time: we register the maximum *absolute* variation of the velocity (thus, considering both accelerations and decelerations), in periods of 5 s; we report this variation, averaged over all simulations, as a function of the vehicles density. Not surprisingly, NaSch and VDR models exhibit the same speed variation, since they use very similar velocity-update rules. Despite it applies different rules, the TOCA model shows a similar trend: at low densities, the speed is close to the maximum v_{max} and changes are mainly due to random perturbations; at densities around the critical threshold, sporadic traffic jams appear and the velocity variation increases; at high densities, variations reduce again since most vehicles are in a jam. The behavior of the maximum speed variation is completely different for the CM model: in this case, the velocity increase is upper-bounded by the maximum acceleration a, which limits the maximum speed variation to $22\,km/h$ in 5 s, although the model tends to have smaller speed adjustment.

Then, we investigate the network connectivity, starting from the distance between the vehicles. Indeed, if we assume that vehicles are equipped with transmission facilities with a given transmission range, we can evaluate the degree of network connectivity from the inter-vehicular distance distribution. Given the transmission range of a vehicle, the distribution of the distance between consecutive vehicles gives the probability that a transmission fails because it cannot reach any vehicle.

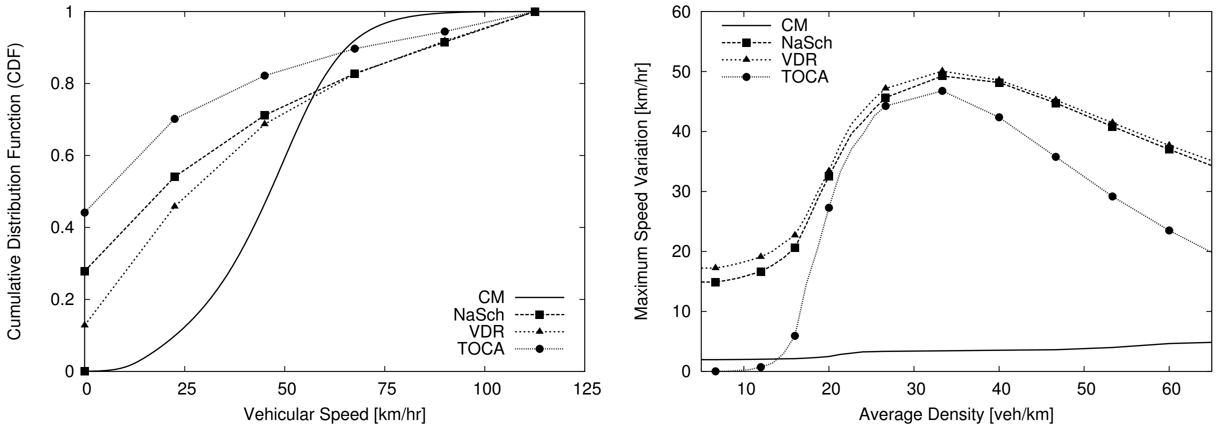

Fig. 3. Vehicular speed distribution at the density $\rho = 45$ veh/km (left) and maximum speed variation in 5 s, averaged over all simulations, as a function of the vehicles density (right)

Left hand-side plot of Figure 4 depicts the probability density function (pdf) of the inter-vehicular distance when the average vehicular density is either low ($\rho = 15$ veh/km) or high ($\rho = 45$ veh/km) for all traffic models. Notice that, although the traffic models lead to different inter-vehicle distance *distributions*, nevertheless the *average* distance is a controlled parameter of the simulation, and is therefore the same for all models. Since in CA models space is stepped in cells, in order to simplify the comparison, the pdf is evaluated at multiples of the cell-length for the CM model too. Results show that, at low densities, vehicles are similarly spaced with every traffic model; conversely, at high densities more important differences between models appear. Considering, for example, a transmission range equal to $R = 200$ m, it is easy to gather from Figure 4 that, despite the gap between vehicles differs from model to model at high vehicular densities, nevertheless the support of the distribution is entirely contained within the transmission range, meaning that the network connectivity is high; conversely, for sparser networks (i.e., at lower densities) the tail of the distribution exceeds the transmission range, thereby we may expect reduced connectivity.

In order to quantify the connectivity properties of the vehicular network, we now proceed as follows. At a given instant of time, after the initial transient, we check the connectivity over the whole road. In particular, we check whether the maximum distance between any two consecutive vehicles is smaller than the transmission range R: if so, all nodes are connected. By iterating this procedure over several snapshots of the system, we measure the probability P that all nodes are connected, which we call *connectivity*.

Right hand-side plot of Figure 4 reports the connectivity P as a function of the vehicular density. Interestingly, it can be observed that the two-phases behavior, which characterized the *vehicular* traffic properties, also persists when *inter-vehicular* connectivity properties are considered. In other words, for very low vehicular densities, it can be seen that vehicle to vehicle communication fails with a significant probability (connectivity P is smaller than 0.5); conversely, for vehicular densities above the critical threshold, all the nodes are connected with very high probability ($P \to 1$). Notice also that for values of the density around the critical density, the models lead to quite different degrees of connectivity, varying from $P = 0.7$ of the CM to $P = 0.85$ of the NaSch model.

V. Beaconing and Position-based Re-Broadcast (BPR)

In this section we evaluate the impact of the previously described mobility models on the broadcast communication paradigm commonly used by different services in inter-vehicular networks. Our focus is on position-based algorithms that use beacon (or HELLO) packets to discover and maintain neighbor relationships, whereas we disregard position-based beaconless solutions such as [15], [16]. Indeed, the use of beacons as a mean to exploit quite accurate position information rather than maintaining complex global topological information is gaining popularity in both academic [17] and corporate [1] research for both *unicast* as well as *broadcast* inter-vehicular communications. In the case of unicast communications, position-based routing [18], [19] relies on the knowledge of the *geographical position* of nodes; broadcast communications adopt the beaconing service essentially for the higher system reliability

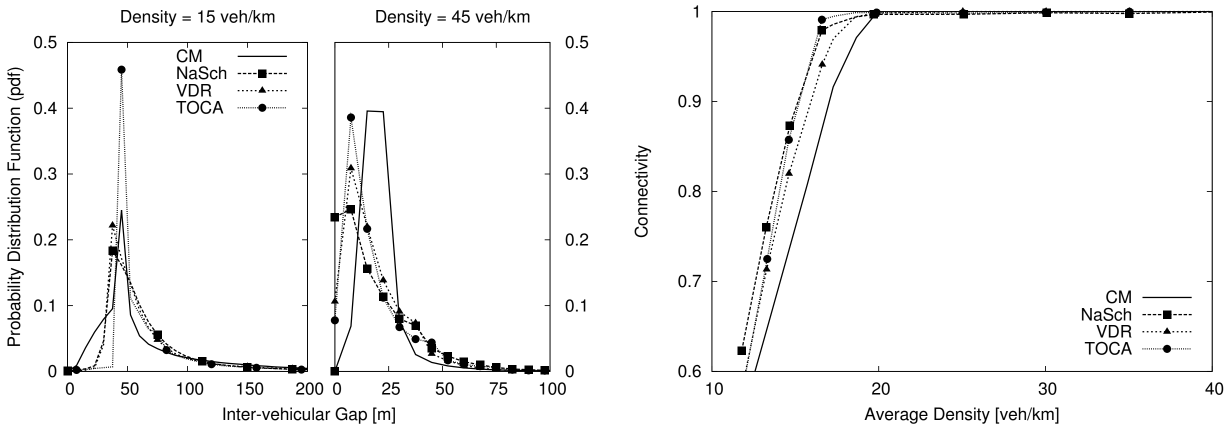

Fig. 4. Probability density function of inter-vehicular distance (left) and connectivity versus the vehicles density (right)

that can be achieved through the knowledge of neighborhood within a one- or two-hops radius [4]. Both cases require that vehicles are equipped with the Global Positioning System (GPS).

In the following, we assume that all the vehicles perform a beaconing procedure or, equivalently, that a position-based routing protocol, based on beaconing, is adopted by the on-board communication device. We adopt the common beacon packet format and the standard beaconing procedure described in the literature. Every vehicle caches the beacon information along with the time of its reception, which will be later used to estimate the neighbor's position. The inter-beacon transmission interval B is usually a *fixed* value between 1 s and 5 s; in the following, we restrict our attention to $B = 5\,\mathrm{s}$ that is a worst-case for our analysis. Moreover, in order to avoid synchronization and beacon collisions, we jitter the transmission of each beacon as in [18], so that the inter-beacon transmission time is uniformly distributed in $[0.5B,\, 1.5B]$.

A. *The generic* BPR *algorithm*

The basic idea of any BPR algorithm is that, whenever some information that has to be broadcasted is received, each node estimates the position of its neighbors by exploiting the information previously exchanged at the routing layer through the use of HELLO packets: the neighbors' position estimate is then used to decide whether a message should be forwarded or not. The forwarding decision aims at trading-off the number of transmitted messages and the probability to inform the vehicles. The optimal trade-off consists in having that only the furthest vehicle that received a message forwards it. We assume that broadcast packets carry: i) the GPS position of the transmitter, ii) its transmission range, iii) the time the broadcast transmission initiated, iv) the original source node identifier as well as v) a randomly chosen packet identifier, assigned once by the original source. Therefore, by caching received broadcast packets IDs for a fixed time-window, every node can limit the forwarding of any broadcast message to at most once per time-window.

We stress that our focus is to evaluate the impact of the different traffic models on the performance of the *class* of algorithms that base their re-broadcast decision on beaconing and on position estimation. As representative of the BPR class, we selected the algorithm in [20], here briefly described. When a node receives a broadcast message from one of its neighbors it performs the following steps:

- it estimates the additional *coverage zone* that it would provide in case it decided to re-broadcast the message: since the actual transmitter position and its transmission range is piggybacked in the broadcast packet, the coverage zone can be precisely evaluated;
- it updates the estimate of its *neighbors positions*, using their speed and location gathered from the last received beacon: the actual position is estimated as the position at the beaconing time increased by the distance traveled at a constant speed, equal to the one reported in the beacon during the time elapsed since the beacon reception;
- it identifies the *closest* among its *preceding* neighbors, and decides to rebroadcast the message if it estimates that the closest preceding neighbor is *outside* the coverage range of the current broadcast packet: in other words, it forwards the message if it believes to be the furthest possible informed vehicle.

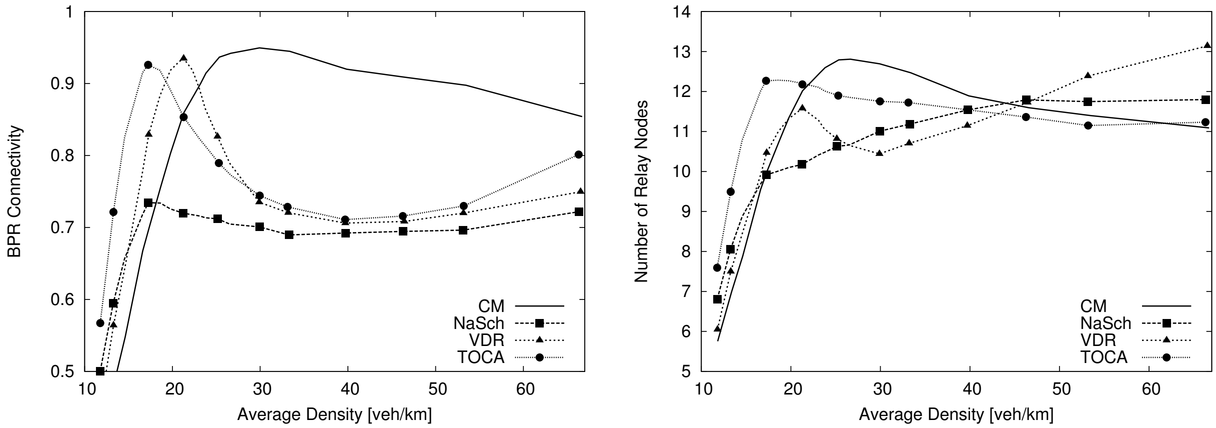

Fig. 5. Fraction of BPR-informed vehicles (left) and number of BPR relay nodes (right) versus the vehicles density

Intuitively, BPR algorithms aim at exploiting the position information to minimize the number of messages needed to successfully broadcast a message to all vehicles: indeed, the number of unnecessary transmissions is minimized if only the last node in the current message transmission range forwards the message. Observe that errors on the estimation of the neighbors position have negative impact on the performance. In particular, the *sign* of the error leads to opposite consequences: over-estimating the distance of a neighbor raises the number of unnecessary relay nodes, whereas distance under-estimation reduces the number of informed vehicles.

B. Performance

In order to evaluate the impact of the vehicular traffic models on the networking performance, we instrument the discrete event simulator described in Section IV to implement ad hoc broadcast communication. We represent the propagation of a single broadcast message on a road of 2 km. We assume that vehicles have wireless devices on-board and transmit 1000 Bytes long broadcast messages at a 2 Mbps rate over a transmission range equal to $R = 200\,\text{m}$, and that the wireless medium is error-free. For what concerns the MAC protocol, nodes are equipped with carrier sense capabilities and adopt a 1-persistent Carrier Sense Multiple Access (CSMA) mechanism. In order to avoid collisions, they sense whether the channel is busy before starting a transmission: in case the channel is busy, the message transmission is delayed, for an amount of time slots (that are $20\,\mu$s-long) uniformly distributed between zero and the contention window size W$= 31$, until the medium is sensed idle.

We point out that the most important cause of error in the BPR position estimation, beside quantization errors, is represented by the driver behavior: specifically, estimation errors are proportional to the difference between the advertised beacon speed and the actual traveling speed in the time steps after the beaconing occurred. Intuitively, we expect the BPR algorithm performance to be affected by the dynamic of the vehicular traffic: indeed, the more the vehicles are likely to change their speed after the beaconing, the less accurate is the information contained in the neighbor table and, possibly, the more prone the algorithm is to inefficiencies.

Figure 5 reports the performance of the BPR algorithm expressed in terms of the connectivity (left) and of the number of relay nodes (right). It can be seen that the adopted traffic model has a dramatic impact on the connectivity, defined as the ratio of the nodes that received the message over all the nodes in the considered road portion. Two interesting remarks can be made. First, the *class* of the vehicular traffic model is of critical importance. Not surprisingly, continuous space models of the CM class are beneficial to the position estimation since they smooth both position estimation errors as well as the velocity updates. Second, the specific CA behavioral rule has an important impact as well: although the underlying traffic dynamics are far from being of simple interpretation, the larger driver's horizon in TOCA and a more significant deceleration at higher speeds on VDR are responsible for peaks around the critical density threshold. Traffic models also differently impact the number of relay nodes: indeed, while the connectivity is similar for TOCA and VDR mobility models, the number of relay nodes varies in the two cases. For high densities the two models have even opposite behaviors: VDR traffic causes BPR algorithms to over-estimate the distance from the closest preceding neighbor (which would be actually within the radio range of the currently received packet) and thus to over-react – while exactly the opposite happens for the TOCA model.

VI. Conclusion and Discussion

This paper focuses on the impact of vehicular traffic models on the performance of broadcast algorithms. After providing a detailed description and comparison of some of the most popular microscopic mobility models presented in the literature, we analyze the performance of inter-vehicular communication systems from a networking point of view, considering both network connectivity as well as the performance of a beaconing and position-based re-broadcast approach. Through simulation, we showed that the adopted vehicular traffic model had only a limited impact on the network connectivity. This is particularly interesting if we consider that re-broadcast schemes based on *instantaneous* decisions are mainly driven by the network connectivity. For example, some of the schemes in [4] base their re-broadcast decision on the evaluation of the *additional coverage* that would be provided by the actual message re-broadcast – and the additional coverage is evaluated solely based on network properties that can be inferred from the information brought by the incoming packet. In these cases, no matter if the vehicular traffic model uses coarse-grained space (as for CA models) or continuous space (as for the CM model), the information carried by the received packet is correct at the time of the reception and the performance of the broadcast scheme is thus rather insensitive to the specific adopted traffic model. On the contrary, schemes based on information collected some time in advance, as the algorithms of the BPR class, are quite sensitive to the employed traffic model; indeed, it is the traffic model which determines the possible changes in the vehicle space, that translate into an inaccurate estimation of the parameters on which the re-broadcast decision is based. To summarize, when evaluating a broadcast scheme, researchers should be aware that, while simpler approaches relying on instantaneous information are quite insensitive to the specific traffic model employed, for evaluating more complex schemes (e.g., such as the ones that are based on beaconing) a careful choice of the traffic model should be performed.

Acknowledgments

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