The Networking Shape of Vehicular Mobility

ABSTRACT

Mobility is the distinguishing feature of vehicular networks, affecting the evolution of network connectivity over space and time in a unique way. Connectivity dynamics, in turn, determine the performance of networking protocols, when they are employed in vehicle-based, large-scale communication systems. Thus, a key question in vehicular networking is: which effects does nodes mobility generate on the topology of a network built over vehicles? Surprisingly, such a question has been quite overlooked by the networking research community. In this paper, we present an in-depth analysis of the topological properties of a vehicular network, unveiling the physical reasons behind the peculiar connectivity dynamics generated by a number of mobility models. Results make one think about the validity of studies conducted under unrealistic car mobility and stimulate interesting considerations on how network protocols could take advantage of vehicular mobility to improve their performance.

Categories and Subject Descriptors

C.2.1 [Computer-Communication Networks]: Network Architecture and Design – network topology, wireless communication; I.6.4 [Simulation and Modeling]: Model Validation and Analysis

General Terms

Performance, verification

Keywords

Vehicular networking, mobility modeling, network topology

Marco Fiore’s research was supported by Regione Piemonte through the “Vehicle-to-Vehicle-to-Infrastructure Communication for Sustainable Urban Mobility” (VICSUM) project.

Jérôme Härri acknowledges the support of the German Ministry of Education and Research (BMB-F) to the “Network-on-Wheels” project under contract no. 01AK064F, and of the state of Baden-Württemberg, Tschira Foundation, PTV AG and INIT AG to the research group on Traffic Telematics.

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1. INTRODUCTION

Vehicular environments represent a challenging but fascinating scenario where infrastructure-based, ad-hoc and hybrid wireless networking paradigms could be applied. Accordingly, the research community has been devoting a growing effort to the study of networking solutions oriented to Inter-Vehicle Communication (IVC).

The distinguishing characteristic of vehicle-based networks is the high-speed, driving rules-constrained, road topology-limited mobility of their nodes. As a matter of fact, the motion of cars in everyday traffic is very different from that of nodes participating in other kinds of mobile networks, and influences the physical topology of vehicular networks in a unique way. Since communication protocols are strongly affected by the underlying connectivity structure, the study of the topological properties of a network built over moving vehicles is a basic step toward a full understanding of the behavior of networking techniques applied to IVC scenarios. However, the common approach to the analysis of the effects of car traffic dynamics in vehicular networks is afflicted by three bad habits.

First, studies on the relationship between protocol performance and vehicular mobility often employ mobility models whose level of realism is questionable or, more generally, not discussed appropriately. This practice can easily raise doubts on the validity of the results obtained, as well as on their applicability to the real world.

Second, evaluations on the impact of mobility are conducted on the performance of MAC, routing or even higher layer protocols, and the topological properties of the underlying vehicular network are derived as an explanation to the networking protocol operations. This “reverse” approach, that involves the study of protocols behavior without a proper knowledge of the network connectivity features, is a complex task, not to mention the implicit risk of drawing biased or wrong conclusions.

Third, results are usually presented as averages over space and time, a choice that, if providing an immediate flavor of the overall system performance, completely loses track of the spatial diversity of vehicular traffic and its evolution over time. As a consequence, analyses limited to mean values cannot capture the localized effects introduced by vehicular mobility, such as same- and opposite-direction car flows, queuing at intersections, and road-dependent traffic congestion conditions.

The objective of this work is thus to improve our knowledge of the topological properties of a network built over nodes moving according to realistic vehicular mobility models, through a rigorous low-level study of the network connectivity.

More specifically, two are the main contributions of this paper:

1. a clear demonstration of the level of realism achieved by different classes of vehicular mobility analytical descriptions, and evidence that such models lead to dissimilar topological properties. The outcome is a strong motivation in favor of
the employment of realistic models to the detriment of approximate descriptions;

2. a detailed study of the connectivity properties of vehicular networks in urban environments, which provide the most interesting and challenging background for network topological studies. We explain not only how the diverse models impact on connectivity metrics, but also why it is so. The search for the physical reasons behind the diverse network topology behaviors forces us to leave analyses of averages and move towards a per-traffic situation study. The results obtained provide a more definite understanding of the impact of mobility on vehicular network topologies, which could be exploited to better explain the performance of existing protocols, as well as to design new IVC networking schemes.

The paper is structured as follows. After briefly reviewing related work in Sec. 2, we address the issue of the realism in vehicular mobility modeling in Sec. 3, testing a variety of models commonly employed in network simulation against benchmark traffic flow theory tests. Then, in Sec. 4, we discuss the impact of these models on the topology of a vehicular network, introducing connectivity metrics of interest and explaining how and why different mobility descriptions produce diverse connectivity dynamics at link and network level. Finally, Sec. 5 concludes the paper.

2. RELATED WORK

Almost any paper on vehicular networks contains a section about the impact of mobility on the networking solution(s) it studies or proposes. However, the content of such sections usually suffers from the problems previously mentioned, relying on unrealistic mobility, protocol-derived results, and averages-based analyses.

Mahajan et al. [1] attempt to understand the effects that mobility models characterized by diverse level of details have on the performance of vehicular ad-hoc networks. However, their analysis is affected by all of the issues identified before, as it relies on movement descriptions of unproven realism, is driven by protocol performance evaluation, and only accounts for mean values. Similar remarks apply to the thesis of Kumar and Dayal [2], who compare the performance of ad-hoc vehicular networks under different mobility models, and to work by Jaap et al. [3], employing realistic cars’ motion representation but still entrusting average results from routing level statistics.

Closer to our approach, Bai and Helmy [4, 5] study the impact of nodes mobility on the topology of ad-hoc networks, by means of a protocol-independent characterization of connectivity. However, their contribution in that sense is part of a larger framework aimed at explaining the performance of routing protocols in mobile ad-hoc networks, and thus suffers from a low level of detail. Also, these works only consider completely random motion representations and very approximated vehicular mobility models, inducing results hardly applicable to real-world vehicular networks.

Also Bohacek and Sridhara [6] address the issue of the relationship between the mobility of nodes in ad-hoc networks and the resulting connectivity graph properties. However, they focus on pedestrian mobility and on the effects of propagation on indoor users’ isolation, with limited attention to vehicular mobility.

In [7], Wisitpongphan et al. employ a realistic analytical motion representation, calibrated on real-world traffic data, in order to determine the degree of connectivity between vehicles traveling on a highway, and to devise appropriate routing techniques. However, their study is limited to a unidimensional space and does not consider interactions between different vehicular flows, thus providing very different results with respect to those obtained in urban environments. Moreover, Wisitpongphan’s analysis also relies on mean values. An analytical characterization of the connectivity of highway-based vehicular networks can be found in a work by Ukkusuri et al. [8] as well.

Some studies on the connectivity in vehicular transportation systems can be found in literature on Delay Tolerant Networks (DTNs). In that context, however, results focus on portraying the distribution of inter-contact times and connection durations between individual pairs of nodes, in order to understand the capacity of car-based “store, carry and forward” communication systems. Thus, small attention is paid to the evolution over space and time of the vehicular network as a whole. Also, DTNs are usually built over a precise subset of vehicles (e.g., buses [9] or taxis [10]), and therefore are not representative of large-scale vehicular ad-hoc networks, envisioned instead to achieve high penetration rates.

Recently, in his thesis [11], Sommer verifies some topological properties of vehicular networks, under different car mobility descriptions, ranging from completely random models to realistic motion representations. Sommer’s analysis is conducted on a very large scale, allowing him to capture network-level connectivity dynamics, but not to discuss link-level phenomena induced by the diverse mobility descriptions. Moreover, the arbitrary, although realistic, road layouts selected for the evaluation prevent a generalization of the results. In that sense, it is however interesting to note that, despite the different scale and road topologies considered, our conclusions on network-wide connectivity properties of vehicular networks under differently realistic mobility models are consistent with those presented by Sommer.

As a final remark, we stress that the limited relation between the aforementioned related work and the approach we adopt in this paper let us think that our perspective is novel in the field of vehicular networking.

3. MODELING VEHICULAR MOBILITY

Mobility modeling is a critical aspect when dealing with vehicular networking. Various approaches have been adopted in modeling the movement of vehicles, and they all undergo a common tradeoff between complexity and detail. A possible classification of models employed in network simulation includes:

- **stochastic models.** Vehicles movement is (i) constrained on a graph representing the road topology, and (ii) random, in the sense that mobile entities follow casual paths over the graph, traveling at randomly chosen speed. Stochastic models are the most trivial way to mimic vehicular mobility;

- **traffic stream models.** Vehicular mobility is observed from a macroscopic point of view and treated as a hydrodynamic phenomenon. Traffic stream models determine cars’ speed by leveraging fundamental physics relationships between the velocity, density and out-flow of a fluid;

- **car-following models.** The behavior of each driver is computed on the base of the state (position, speed, acceleration) of the surrounding vehicles. Car-following models were first employed in the 50’s, and represent the most common way to analytically describe mobility in traffic flow theory;

- **flows-interaction models.** Built upon an instance of one of the previous categories, flows interaction characterizes the mutual dynamics that merging vehicular flows induce reciprocally, e.g., at highway ramps or urban intersections.

Obviously, this classification does not pretend to be fully comprehensive, as it excludes several categories of models (e.g., cellular
automata, behavioral and queue-based descriptions) which, however, provide similar results with respect to the more common car-following analysis, according to traffic flow theory literature. The models employed in this paper were selected in a way to cover all the categories of vehicular mobility descriptions listed above. In the remainder of this Section, we review such models and discuss their level of realism.

### 3.1 Models description

The notation used to formally define the models is summarized in Fig. 1, where the index $i$ refers to the vehicle under investigation, while $i \pm 1$ ($i \pm 1$) identify the front and back vehicles on the current (adjacent) lane, respectively. Furthermore, for a generic vehicle $k$ at time $t$, $x_k(t)$ and $v_k(t)$ represent its position and speed, and $\Delta x_k(t)$ the bumper-to-bumper distance from its front vehicle. Also, we denote models input parameters as $a$ (acceleration), $b$ (deceleration), $v_{min}$ (minimum allowed/desired speed), $v_{max}$ (maximum allowed/desired speed), $\Delta t$ (time step) and $\Delta x_{min}$ (safety distance).

The **Constant Speed Motion** model [12] is a typical example of stochastic traffic as it constrains a generic vehicle $i$’s movement on a given road topology, setting its speed to $v_i = v_{min} + (v_{max} - v_{min}) \eta_i$, where $\eta$ is a uniformly distributed random variable in $[0, 1]$. Trips within the graph are determined by running a shortest path algorithm to a destination randomly selected among the vertices of the grid. Constant Speed Motion also includes the possibility of forcing pauses at intersections encountered within a trip. In that case, the model provides some rudimental flows-interaction mechanisms, as a vehicle arriving at an intersection stops for a time (i) randomly chosen in a given range $T_{i}$, if no node is waiting at the intersection, or (ii) equal to the residual pause time of the first node waiting at the same intersection. That way, nodes paused at at road junction leave the intersection all together, mimicking the clustering of vehicles leaving the same intersection, a typical effect in real world traffic. In our tests we employ two versions of Constant Speed Motion, without (CSM) and with (CSM w/ pauses) pauses at intersections.

The **Manhattan** model [4] also falls into the stochastic category. It adds complexity to the speed management with respect to CSM, updating cars’ velocity according to

$$v_i(t + \Delta t) = \begin{cases} v_{i+1}(t) - a/2, & \text{if } \Delta x_i(t) \leq \Delta x_{min} \\ \tilde{v}_i(t + \Delta t), & \text{otherwise} \end{cases}$$

where $\eta$ is the same uniform random variable introduced before. Manhattan thus adds some acceleration-bounded randomness in the velocity update, and, from Eq. 1 above, imposes speed limitation to avoid overlapping of vehicles. However, Manhattan lacks CSM’s pause handling at intersections.

The **Fluid Traffic Motion** (FTM) model [13] adopts a traffic stream approach on a microscopic level. It describes the speed as a monotonically decreasing function of vehicular density, forcing a lower bound on speed when the traffic congestion reaches a critical state.

$$v_i(t + \Delta t) = \max \left\{ v_{min}, v_{max} \left( 1 - \frac{n_i(t)}{k_{jam}} \right) \right\}$$

Eq. 3 describes the model, where $k_{jam}$ is the vehicular density for which a traffic jam is detected, $n$ is the number of cars on the same road of $i$ and $l$ is the length of the road segment itself. Since $n/l$ is the current vehicular density of the road, cars traveling on very crowded streets are forced to slow down, possibly to the minimum speed, while, when less congested roads are encountered, the speed of cars is increased towards the maximum value.

The **Intelligent Driver Model** (IDM) [14], is an embodiment of the car-following category. IDM characterizes a vehicle behavior through its instantaneous acceleration.

$$\frac{dv_i(t)}{dt} = a \left[ 1 - \frac{v_i(t)}{v_{des}} \right]^4 - \frac{\delta}{\Delta x_i(t)} \right]$$

$$\delta = \Delta x_{min} + \left( \frac{v_i(t)}{T} + \frac{v_i(t)(v_i(t) - v_{i+1}(t))}{2\sqrt{a\Delta t}} \right)$$

The desired speed $v_{des}$ is different for each driver, and it is uniformly distributed in $[v_{min}, v_{max}]$. Eq. 4 models the local acceleration on two contributions: the speed increase to reach the desired velocity $v_{max}$ on a free road $[1 - (v_i(t)/v_{max})^4]$, and the deceleration induced by the preceding vehicle $(\delta/\Delta x(t))^2$. The so called desired dynamical distance $\delta$, which determines the braking term, depends on the absolute and relative speed of vehicles, as shown in Eq. 5, where $T$ is the safe time headway.

The **IDM with Intersection Management** (IDM-IM) [15] is a flows-interaction model which adds intersection handling to the car-to-car interaction description provided by IDM. The IDM-IM model can manage crossroads regulated by stop signs or traffic lights, by tweaking the IDM model parameters of the first vehicle on each road at a time $t$ as follows

$$\Delta x_i(t) = \Delta x_{stop}(t) - S, \quad v_{i+1}(t) = 0$$

where $\Delta x_{stop}(t)$ is the current distance to the intersection and $S$ is a safety margin, accounting for the gap between the center of the intersection and the point the car would actually stop at. Thus, compared to the IDM, the distance from preceding vehicle is substituted by the distance to the point the vehicle has to stop at. On the other hand, the speed difference is set to the current speed of the car $v_i(t)$, so that the stop sign is seen as a still obstacle. We refer the interested reader to [15] for a detailed description of the model. We distinguish between two versions of IDM-IM in our performance evaluation, depending on whether intersections are regulated by stop signs (IDM-IM w/ stops) or traffic lights (IDM-IM w/ lights).

The **IDM with Lane Change** (IDM-LC) [15] further extends the flows-interaction description of IDM-IM, by adding overtaking capability to vehicles. IDM-LC is based on the MOBIL lane changing model [16], which, by following a game theoretical approach, allows a vehicle to move to an adjacent lane if its advantage, in terms of acceleration, is greater than the disadvantage of the back car in the new lane:

$$\frac{dv_i(t)}{dt} - \frac{dv_j(t)}{dt} \geq p \left( \frac{dv_{i-1}(t)}{dt} - \frac{dv_{j-1}'(t)}{dt} \right) + a_{thr},$$

where terms marked with a ‘$\prime$’ represent values after the potential change of lane. In Eq. 6 the left hand side of the inequality is
the advantage that the lane change would bring to the car under study and the right hand side represents the disadvantage brought by the same movement to the back car in the new lane. The $p$ factor models the driver’s politeness, while the acceleration threshold $\alpha_{th}$ prevents lane hopping phenomena in borderline conditions and can be adjusted to differentiate movements to the left or to the right. Eq. 7 introduces a safety condition on the braking deceleration of the back car in the new lane. Since IDM-LC requires multiple lanes while the previous models only employ one lane per direction, we provide a fair benchmark to IDM-LC by means of a modified IDM-IM running over a multi-lane topology, but not performing any change of lane (IDM-IM multilane). This allows us to separate the effects due to the increased road capacity and the actual lane change capabilities of the model.

### 3.2 Realism of models

In vehicular mobility modeling, “realism” is a model’s ability to reproduce traffic phenomena as observed in the real world. An interesting question one could pose is: what is the level of realism of the different categories of models? Since the goal of vehicular network simulations is to produce results as near as possible to those that one would obtain with actual deployments, the issue of realism plays a key role in vehicular mobility modeling. The aim of this Section is thus to provide an answer to the above question.

We employed classic benchmark tests from vehicular traffic flow theory to validate models belonging to the different categories. In particular, we selected four tests, which verify the capability of models to reproduce real-world (i) fundamental diagram, (ii) reaction to a perturbation, (iii) shockwave effect, and (iv) intersection speed profiling. The Manhattan, FTM, IDM and IDM-IM w/ stops models were selected as representative of each category, and their parameters set as summarized in Tab. 1. We stress that in the first three tests IDM and IDM-IM generate identical results.

The first test verifies the capability of a model to correctly recreate the fundamental relationship between vehicular out-flow, speed and density. Given a straight road, as the in-flow rate, and consequently the car density, increases, the out-flow of vehicles is expected to grow linearly at first. When a critical vehicular density is reached, the road capacity does not sustain the arrival rate anymore, leading to queuing phenomena that slow down the system.

![Figure 2: Vehicular out-flow vs density (left column), speed vs density (middle column) and speed vs out-flow (right column) diagrams generated by the Manhattan (top row), FTM (middle row) and IDM (bottom row) models](image)

Results from this test are depicted in Fig. 2, where it appears evident that IDM and FTM behave as expected, while the Manhattan model generates an unrealistic, persistently linear relationship between the three variables.

Secondly, we tested the reaction of the models to a mild perturbation, monitoring the behavior of a flow of cars traveling on a single-lane road and encountering a slow vehicle ahead. A real-world behavior would involve the vehicles slowing down (each with different dynamics, as the first vehicle brakes the hardest, while the following experience progressively smoother decelerations) and forming a queue as they approach the obstacle. Then, when the obstacle is removed, cars should start accelerating again, with a speed increment which is propagated along the queue. This is what can be...
observed in Fig. 3 for the IDM model. When following the Manhattan model, vehicles slow down suddenly in presence of the obstacle, and, after it is removed, do not accelerate back to full speed due to the model’s lack of desired speed. The FTM model only generates a very rough reproduction of the correct behavior, with deceleration when the intersection comes into driver’s sight, and proper acceleration while leaving the stop sign.

From the results presented above, we can conclude that, while car-following models provide a faithful representation of real world vehicular dynamics, stochastic models fail all the tests and cannot be considered realistic reproductions of vehicles behavior in everyday traffic. Traffic stream models, on the other hand, achieve partial success, since they are intended to reproduce large scale phenomena, but are inadequate when microscopic car interactions are taken into account.

4. MOBILITY AND CONNECTIVITY

Having clarified the level of realism of the different models under examination, we can proceed to the analysis of their impact on the topology of a vehicular network. Our goal is to understand if, how and why different mobility descriptions affect general, protocol-independent, low-level properties of the network connectivity.

To this end, we define several metrics through which to derive network topological properties of interest, and show that different analytical representations of traffic motion have a non-negligible impact on such metrics. Explaining why this happens leads us to an in-depth analysis which further evidences the microscopic-scale differences in the vehicular traffic generated by diverse mobility models.

As our focus is on nodes mobility, we avoid at first biases that could be introduced by complex road topologies and non-uniform traffic, by studying a simple grid-like street layout. Then, we extend the results by scaling the scenario size and road length, considering irregular topologies and varying the density and pattern of traffic.

4.1 Metrics

As stated before, our analysis requires metrics capable of capturing the dynamics of the physical topology of a potential network built over moving vehicles. For the formal definition of such metrics, we model the network topology at time $t$ as a graph $G(t) = \{V, E(t)\}$, where vehicles (also referred to as nodes in the following) correspond to the set of vertices $V = \{v_i\}$ and communication links to the set of time-dependent edges $E(t) = \{e_{ij}(t)\}$. An edge $e_{ij}(t)$ exists if there is a direct wireless communication link from $v_i$ to $v_j$ at time $t$, with $i \neq j$. Using this notation, we define the following metrics:

- **Link duration.** The time span between the instant at which a vehicle enters within transmission range of another vehicle, and the instant at which the physical connection is lost, due to the relative movement of nodes. Formally, the duration of the link from $v_i$ to $v_j$ at time $t$ is defined as

$$l_{ij}(t) = \begin{cases} 0, & \text{if } \exists e_{ij}(t) \\ t_f - t_0, & \text{if } \exists e_{ij}(t), \end{cases}$$

with $t_0, t_f$ such that $\exists e_{ij}(t_0), \nexists e_{ij}(t_f)$ and $\exists e_{ij}(\tau), \forall \tau \in [t_0, t_f]$. The link duration measures how stable a connection is over time;

- **Nodal degree.** The number of vehicles within the transmission range of a node, i.e., the number of neighbors of the node. If the set of neighbors, both symmetric and asymmetric, of $v_i$ at time $t$ is defined as

$$N_i(t) = \{v_j| \exists e_{ij}(t)\},$$

then the degree of $v_i$ at the same time is given by $d_i(t) = |N_i(t)|$. The nodal degree determines how dense is the network, from the physical connectivity point of view;
- **Cluster number.** The number of co-existing, non-connected clusters of nodes at a given instant. We define a cluster as a group of vehicles which is logically fully connected, i.e., within which a bidirectional (multihop) route exists between whichever couple of nodes. Formally, the existence of a unidirectional path from $v_i$ to $v_j$ at time $t$ can be represented as the binary variable

$$p_{ij}(t) = \begin{cases} 1, & \text{if } \exists e_{ij}(t) \text{ or } \exists v_k | \exists e_{ik}(t), \exists e_{kj}(t), \exists v_l | \exists e_{jl}(t), \exists e_{lk}(t) \in C(t), \forall j < i, \\ 0, & \text{otherwise.} \end{cases}$$

The cluster in which $v_i$ lies at time $t$ can be defined as

$$C(t) = v_i \cup \{v_j | p_{ij}(t) = 1, p_{ij}(t) = 1\},$$

and the set of unique clusters in the network at $t$ as

$$C(t) = \{C_i(t) | C_i(t) \cap C_j(t) = \emptyset, \forall j < i\}.$$

The cluster number corresponds to the cardinality of this last set, $c(t) = |C(t)|$, and provides information on the degree of fragmentation of the overall simulated network, in terms of number of mutually isolated groups of nodes;

- **Normalized cluster size.** The number of vehicles in a cluster at a given instant, normalized over the number of simulated vehicles. For a cluster $C_i(t)$, it can be defined as

$$s_{C_i}(t) = |C_i(t)|/|V|.$$

The normalized cluster size characterizes the distribution of nodes into clusters, distinguishing clusters of different cardinality, and it is independent from the simulated network size;

- **Clustering coefficient.** An index of the connectivity of vehicles within a cluster. Formally, if we define the set of links within a cluster $C_i(t)$ as

$$E_{C_i}(t) = \{e_{ij}(t) | v_j \in C_i(t)\},$$

then the clustering coefficient of the same cluster is

$$k_{C_i}(t) = \frac{|E_{C_i}(t)|}{|C_i(t)|(|C_i(t)| - 1)},$$

which is the ratio between the number of existing links and the maximum number of unidirectional links which could exist in the cluster. According to this definition, the clustering coefficient has a maximum value 1 if the cluster is a clique, while it tends to zero in a linear topology with a number of nodes drifting to infinity.

### 4.2 Mobility models analysis

Mobility models determine the way nodes move in a vehicle-based network and, as a consequence, the connectivity properties of the resulting system. Thus, they represent the first aspect that has to be taken into consideration when exploring the relationship between vehicular motion and network topology. At the same time, urban environments are the most attractive scenarios for studies on such a relationship, due to the amount and complexity of car interactions they involve.

In order to determine the impact of vehicular mobility modeling on the connectivity of an urban network, we employ a deliberately simple scenario. The rationale behind this choice is that a plain environment evidences at best differences which are solely attributable to the mobility description, avoiding any bias that complex road topologies and activity models could induce.

Thus, we simulate a regular 3x3-block grid, each block measuring 250 m of side. Vehicles enter/leave the scenario from the borders of the topology and randomly select their trips. A typical vehicular density of 20 vehicles/km/lane is considered, and a transmission range of 100 m is assumed. Models parameter settings are reported in Tab. 1. Due to space limitations, we cannot provide an in-depth discussion of models settings calibration, and invite the interested reader to refer to the models’ references for details. We just stress that the selected parameters fit real-world values and that we calibrated them according to the simulated scenario.

#### 4.2.1 Network-level analysis

We start our analysis from the clustering metrics, which reflect network-wide connectivity properties. Fig. 6 reports the cluster number, normalized cluster size and clustering coefficient, averaged over space and time, relative to different mobility models.

As a first observation, it is evident that diverse motion descriptions generate dissimilar network clustering dynamics, and can be ordered by increasing average cluster number, which coincides with increasing clustering coefficient and decreasing normalized cluster size. This relationship between the clustering metrics is expected, since the number of simulated vehicles is the same for all the models, and a higher number of non-communicating clusters implies a smaller size of each cluster. Also, clusters of fewer vehicles tend to experience slightly higher degree of internal connectivity, as their spatial extension is reduced, and the probability that two vehicles in the cluster are out of transmission range is lower.

Secondly, by looking at the individual models, it is clear that the sequence follows a precise scheme: models which neglect flows interaction (CSM, Manhattan, FTM, IDM) come first, generating fewer, larger clusters, i.e., a more globally connected network, in which the probability that two nodes over the road topology cannot communicate is low. On the other hand, motion descriptions which consider intersection management and employ multiple-lane roads (IDM-IM multilane, IDM-LC) determine the highest cluster numbers, fragmenting the network into smaller and more isolated groups of nodes. Models featuring flows-interaction handling but forcing the vehicular traffic over single-lane roads (CSM w/ pauses, IDM-IM w/ stops, IDM-IM w/ lights) result in an intermediate behavior.

To understand why the analytical representations of movement have such an impact on the network clustering, a spatial analysis is required. To this end, Fig. 7 shows the vehicular density measured over the simulated road topology, averaged over time, for a significant subset of the models.

We can notice two main trends: models neglecting flows interaction tend to produce quasi-uniform distributions of vehicles, while models accounting for intersection management result in peaks of vehicular density at crossways which slowly smooth down to lower density elsewhere.

The first behavior is symptomatic of a presence of cars spread...
over the road topology, at each instant of simulation. From the network connectivity point of view, this leads to the creation of a few, large clusters, as it is hard to find gaps in the vehicular instantaneous distribution that are larger than the nodes transmission range. The higher average cluster number obtained with the Manhattan model with respect to CSM, FTM or IDM, even in presence of a similar vehicular distribution, is attributable to the lack of desired speed of the model, which, coupled with its non-overtaking rules, creates small clusters of cars traveling at low speed over the road segments.

On the other hand, when considering stop signs or traffic lights at road junctions, the accumulation of vehicles waiting at crossways tends to create clusters around these locations, while the lower density over roads eases the absence of communication paths along the streets that join the intersections. This effect is more evident when employing stop signs than traffic lights, as the firsts are slower in granting passage to vehicles and thus produce a higher congestion at intersections. Moreover, the presence of multiple lanes magnifies the clustering effect at intersections, as they allow vehicles to gather nearer to the road junctions, forming shorter, denser queues. The latter is the reason why IDM-IM multilane and IDM-LC result into a higher average cluster number with respect to the other flows-interaction models, as seen in Fig. 6.

CSM w/ pauses falls in between the uniformly distributed and intersection clustering behaviors identified above, as it adds unrealistically abrupt and high (notice the different density scale in Fig. 7) peaks at intersections, while a perfectly uniform distribution of vehicles is measured along the roads.

### 4.2.2 Link-level analysis

The diverse vehicular distributions result in noticeable differences also when looking at communication link properties, as evidenced in Fig. 8, showing the average nodal degree and link duration obtained with the various mobility models. Models producing quasi-uniform densities have comparable performance in terms of nodal degree and link duration, and the same is true for models considering traffic lights-ruled intersections (IDM-IM w/ lights, IDM-IM multilane and IDM-LC). In the latter case, the link duration and the nodal degree are almost doubled with respect to the first group of models. Evidently, the presence of flows interaction management at road junctions forces vehicles to stop, increasing the average duration of links, and creates high-density spots, where vehicles enjoy an elevate number of neighbors. CSM w/
employed to distinguish different driving situations involving two
models neglecting flows interaction is characterized by a very reg-
cular maxima, instead of one. CSM w/ pauses (II) generates a PDF re-
overlapping PDFs (III), which are more spread and present two lo-
els which assume traffic light-managed crossways produce almost
ular, single-peaked PDF (marked as I). On the other hand, mod -
Fig. 9, the nodal degree of the network topology obtained fro m
understanding can be achieved considering the respective PDF s. In
as already stated, stop signs slow down flows merging at
traffic lights case.

Averages provide an immediate picture of the effect of mobility
modeling on nodal degree and link duration, however a deeper un-
derstanding can be achieved considering the respective PDFs. In
Fig. 9, the nodal degree of the network topology obtained from
models neglecting flows interaction is characterized by a very reg-
ular, single-peaked PDF (marked as I). On the other hand, mod-
els which assume traffic light-managed crossways produce almost
overlapping PDFs (III), which are more spread and present two lo-
cal maxima, instead of one. CSM w/pauses (II) generates a PDF re-
sembling that of group III, while IDM-IM w/ stops further spreads
the PDF, reducing its regularity.

In order to explain which are the physical reasons behind the
different PDF shapes, we further increase the level of detail of our
analysis. In Fig. 10 we report the evolution of the PDF of the speed
difference between a node and its neighbors (Δv), as the node de-
gree changes. In other words, the plots provide a measure of the
distribution of the speed difference between a node and its neigh-
bors, given the degree of the node. Since the value of Δv can be
employed to distinguish different driving situations involving two
nodes, we can derive from the Δv PDF evolution the typical cir-
cumstances under which a node enjoys a certain degree. Here the
speed difference is intended as the modulus of the speed vectors
difference, and thus accounts for vehicles movement direction.

In particular, we are interested in explaining the shape of the
degree PDF in the case of models belonging to group III, as it gath-
ers the models which more realistically reproduce the case of traf-
fic lights-ruled intersections, frequently encountered in real-world
traffic. From Fig. 10, we can notice that the high-probability nodal
degree values (around 3 and 17 neighbors) correspond to two dif-
ferent Δv PDFs, evidenced by the red and blue lines respectively.
In the case of the first peak, i.e., of the red line denoting a nodal
degree value equal to 3, neighbors relative speed has a high prob-
ability of being very low (less than 5 m/s) or very high (around
25 m/s). These values of Δv respectively identify the cases of
neighbors traveling at full speed on the same lane or on the op-
posite direction with respect to the vehicle whose degree is under
study. Thus, the low-degree peak in the PDF of Fig. 9 occurs when
nodes are traveling along the road segments. On the other hand,
the high-degree peak, matching the blue line at nodal degree equal
to 17, is characterized by a Δv PDF accumulated around two ar-
eas, centered on 0 and 12 m/s respectively. Both these aggregation
points can be associated with the situation in which the node un-
der examination is stopped at an intersection: in the first case, the
neighbor is also waiting, while in the second the neighbor is reach-
ing the road junction from a different direction and crossing it at
full speed. The overall degree PDF of Fig. 9 is thus the result of the
superposition of two highly probable effects: a low-degree connec-
tivity while nodes are traveling at high speed on road segments, and
a high-degree connectivity while they are waiting at intersections.

As far as the other models are concerned, similar plots for the
models of group I show quasi-uniform distributions of Δv for any
value of the nodal degree, as there are no distinguishing driving
situations such as those encountered with flow-interaction models.
CSM w/pauses’ lack of car-to-car interaction also results in flat
Δv PDFs, with the addition of a higher probability of experiencing
a zero Δv due to pauses at intersections. IDM-IM w/ stops’ plot
resembles that obtained with models of group III, but it generates
a much higher probability of having neighbors at zero speed differ-
ence as the nodal degree grows, due to longer queuing at crossways.

The same approach can be applied to the link duration, whose
average values were depicted in Fig. 8. The corresponding PDFs
are shown in Fig. 11. As for the previous metric, also the link
duration distribution is strongly correlated to the mobility model
employed, and four main behaviors can be identified, matching the
same groups of models already distinguished before. Once more,
models disregarding flows interaction (I) generate regular distribu-
tions, whereas traffic light-managed models (III) produce very pe-
culiar double-peaked PDFs. CSM w/pauses (II) approximates the
behavior of models of group III, with lower precision with respect
to the nodal degree metric case. Finally, the presence of stop signs
(IV) spreads the probability over a much larger range than any other
model, almost canceling the low-duration peak.

Focusing on the case of models falling into group III above, the
analysis against the speed difference, in Fig. 12, shows a number of
separate effects. For very low link durations (less than 5 s, as
evidenced by the black line in the figure), the two major contribu-
study offers to network protocols evaluation and development.
in vehicular networking, and the opportunities that a topological
invoke to reflect upon two issues in particular: the need for realism
involved in nodes moving at \( \Delta v \) PDF, localized around 16 s and identified by the red line, has a ma-
jects come from neighbors traveling at relative speeds around 15
ations come from neighbors traveling at relative speeds around 15
Thus, connectivity analyses can contribute to explain the per-
issues, which are consistent with reality. Pseudo-random pauses at
• car-to-car interaction plays a minor role in urban scenarios, when networking metrics are taken into account. As a mat-
• realistic flows interaction at intersections has a dramatic im-
potential that a realistic flows interaction is only built on top of a car-
• employing multiple lanes does not introduce noticeable dif-
• lane changes do not have any noticeable effect on the net-
Thus, the way mobility is modeled has a major impact on the topo-
• protocol performance evaluations conducted on scenarios in which no realistic flows interaction is considered can be easily mis-
• street topology locations are not all equal. Road junctions tend to create dense clusters, hardly connected to each other

4.2.3 Discussion
The results of the network connectivity analysis shown before invite to reflect upon two issues in particular: the need for realism in vehicular networking, and the opportunities that a topological study offers to network protocols evaluation and development.

As far as the first issue is considered, our tests show that:

\[ \Delta v (\text{m/s}) \]

\[ 0 \quad 5 \quad 10 \quad 15 \quad 20 \quad 30 \]

\[ 0.0 \quad 0.1 \quad 0.2 \quad 0.3 \quad 0.4 \quad 0.5 \quad 0.6 \quad 0.7 \]

Figure 12: Speed difference PDF evolution over link duration

Figure 13: Driving situations influencing the link duration

Thus, the way mobility is modeled has a major impact on the topo-
logical properties of a vehicular network, and, apart from over-
takings, all of the motion features (flows merging and the car-to-car in-
teraction it is build upon, traffic light management, multiple lanes)
proved to generate unique cluster- and link-level effects, motivat-
ing the employment of realistic motion representations instead of approximate ones.

On the other hand, when focusing on networking protocols, the results prove that:

• protocol performance evaluations conducted on scenarios in which no realistic flows interaction is considered can be easily mis-

Thus, connectivity analyses can contribute to explain the perfor-
ance of existing protocols, when employed in vehicular environ-
ments, as well as to design new ad-hoc networking solutions, lever-
gaging an improved knowledge of the topology dynamics.
4.3 Other factors affecting mobility

Vehicular mobility modeling is not limited to car interaction management. Factors such as the vehicular density, the road topology size and shape, and the drivers’ activity model all fall within the scope of movement description. Consequently, one could wonder how the results we obtained in the previous analysis are affected by these factors, and if the properties we derived hold in more complex traffic environments. In this Section, we provide an answer by evaluating the impact of the aforementioned mobility aspects on the different models. Due to space limitations, we are only presenting a significant subset of the results for each scenario.

Vehicular density

Vehicular density is a measure of the level of congestion of the road topology. From Fig. 14, depicting the evolution of the normalized cluster size versus the simulated vehicular density, we can notice that an increasing density allows for more connected networks, up to a single large cluster including all the nodes. It is important to notice that the density of cars does not affect the relative properties of the models, on the contrary it magnifies the differences between them. Thus, the considerations we made for a vehicular density of 20 vehicles/km/lane are even more valid for higher densities. Consistently, the cluster number and clustering coefficient tend to decrease with increasing car density, but the relative performance of mobility models stays the same.

When looking at the link duration, in Fig. 15, several models appear influenced by the vehicular density, while others are not. CSM, Manhattan and CSM w/ pauses result in constant curves, as they neglect car-to-car interaction and/or intersection management. FTM, by its own nature, slows the speed of cars as the vehicular density increases, thus generating more durable links. IDMs increase of link duration is just an artifact of the model implementation, forcing vehicles overlapping at intersections to stop: as the density grows this situation occurs more and more frequently, leading to higher link durations. IDM-IM w/ stops and IDM-IM w/ lights also result in longer lasting links, as the queuing at road junctions becomes more evident with a higher car density. The effect is amplified by the slower stop signs with respect to the faster traffic lights. Finally, multilane models (IDM-IM multilane and IDM-LC) also generate quasi-constant lines, however this is attributable to the increased road capacity, which can handle higher traffic congestion without significant effects on queues at crossways. By further increasing the density, even these models would reach a saturation point after which the average link duration would start increasing.

Road topology size

Scaling the road topology size, by considering regular grids composed of a higher number of blocks, affects the absolute value of the clustering metrics, but not the link-level ones. This is confirmed by Tab. 2, reporting the average values measured for the IDM-IM w/ lights model, when road grids of different size are taken into account. We stress that the vehicular density is kept constant at 20 vehicle/km/lane by increasing the number of simulated cars in larger topologies. As the driving situations involving couples of nodes stay the same, no matter the number of intersections in the street layout, both nodal degree and link duration result in almost constant values. On the other hand, network-wide properties are strongly dependent on the road topology, and the cluster number grows along with the number of road junctions. Clusters formed at intersections tend however to have similar internal structures, no matter the size of the grid, as shown by the clustering coefficient.

Identical observations hold in the case that the scaling is operated on a road length basis, by keeping the number of blocks constant and increasing the length of each road segment. From Tab. 3, it is clear that link-level metrics are again very similar through the different experiments, while the clustering properties vary with the length of the streets. The reason behind the increase in the cluster number is that, by further separating the intersections, we reduce the probability that clusters of vehicles gathered at different crossways are connected by vehicles traveling over the road segments.

Irregular roads layout and activity patterns

Considering irregular road topologies affects the network connectivity at a global level, as it leads to different distributions of vehicles over space, as shown in Fig. 16(a), which depicts the average vehicular density obtained with IDM-IM w/ lights on an incomplete 4x4 grid. There, intersections have different importance, depending on their position on the street layout, and are thus characterized by diversely shaped density peaks. Such an effect is magnified by the
presence of a vehicular activity which is not random, but planned, e.g. conveying most of the traffic on two “main” roads, as in the case depicted in Fig. 16(b).

The different vehicular distributions determine, in turn, diverse network clustering properties. This obviously affects network-level metrics, and also the amount of neighbors observed by each vehicle, in Fig. 17. There, random activities of cars generate similar PDFs, no matter the underlying road layout, while a planned activity has a two-fold impact. First, the left PDF peak, attributable to vehicles moving along road segments, is skewed towards higher values, as the planned activity channels most traffic on popular streets. Second, the right PDF peak, representing the contribution of vehicles at intersections, is (i) reduced in terms of probability, since under the planned activity most road junctions are uncongested, and (ii) shifted to a higher degree, as the only congested crossroad is now very crowded.

However, even in presence of non-homogeneous traffic distributions, link duration properties stay unmodified. As a matter of fact, the relative PDFs recorded with varying road topologies and vehicular activities, in Fig. 17, almost completely overlap. As a further proof, the plots showing the evolution of the $\Delta v$ PDF over the link duration with irregular road topology and random (Fig. 16(c)) or planned (Fig. 16(d)) cars activity are almost identical to that observed for the regular grid with uniform traffic in Fig. 12.

We can conclude that vehicular density, road topology size and layout, and activity planning all have a non-negligible impact on the network connectivity. However, link level properties tend to hold, and the results of our low-level analysis on a simpler scenario apply even when more complex environments are taken into account.

5. CONCLUSIONS

We showed that an analysis of the connectivity properties of vehicular networks can evidence how and explain why different mobility models lead to dissimilar network protocol performance. The outcome of our tests motivates the employment of realistic movement descriptions instead of approximate ones, and, at a time, provides insights into the dynamics of a vehicular network topology which could be useful in understanding the performance of existing protocols or in developing novel networking schemes.

6. REFERENCES


