Understanding Vehicular Mobility in Network Simulation

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***Abstract*— Within the extent of recent research activity in the field of vehicular networking, notwithstanding the quantity of simulative studies carried out on protocols performance, the impact of vehicular mobility characterization has been often overlooked. Realistic mobility models are seldom employed, and when used, no comment is usually provided on the different effects that such models have on the results with respect to simpler mobility descriptions. In this paper, we address this issue, and analyze the impact that various levels of details in vehicular mobility modeling have on the simulation of networking protocols.**

I. Introduction

The growing interest toward the possible applications of wireless technologies to the vehicular environment has recently led the networking research community to a significant effort aimed at studying the suitability of both existing and novel ad-hoc protocols to car-to-car and car-to-road communication. Intrinsic difficulties in the conducting of large-scale and extensive field trials of logistic, economic and technological nature, make simulation the mean of choice in the validation of networking protocols for vehicular networks, and a common practice in the preliminary stages of real-world technologies development.

However, quite surprisingly, most of the simulative approaches to the analysis of inter-vehicle communication tend to pay small attention to vehicular mobility, thus neglecting the most characterizing aspect of vehicular networks. As a matter of fact, networking a vehicular environment is made especially challenging by peculiar features of nodes mobility, such as the high speed of cars, the strict constraints on nodes movement patterns, the periodicity of dense and sparse network areas, the clustering of users at intersections or in traffic jams. These phenomena can only be captured with a limited level of realism in the simulated cars movement, and their impacts on the network performance cannot be ignored or assumed apriori, but need to be studied to guarantee the network simulation outcome to be reliable.

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The objective of this paper is thus to understand what degree of interest the networking research community could have toward different mobility models, each of which providing an increasing level of detail in the vehicular movement description. To this extent, we recall in Section II some common mobility models employed in the vehicular networking literature, and we define their level of realism using typical traffic flow theory tests in Section III. In Section IV, the effect of the adoption of different mobility models on inter-vehicle communications metrics is studied. Finally, we wrap up our analysis in Section V.

II. Vehicular mobility modeling in networking

In this Section we briefly introduce the mobility models that will be investigated in the remainder of the paper.

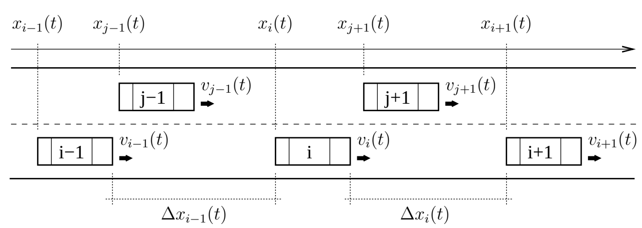


Fig. 1. Vehicular traffic notation.

With reference to the vehicular traffic scenario depicted in Fig. 1, we define as i the vehicle whose behavior is currently under investigation. At a given time instant t, such vehicle is at a position $x_i(t)$, and travels with a speed $v_i(t)$, meaning that its instantaneous acceleration can be expressed as $\frac{dv_i(t)}{dt}$. Index $i+1$ identifies the front vehicle with respect to i, which is located at $x_{i+1}(t)$, and travels at velocity $v_{i+1}(t)$, at time t. The front bumper to back bumper distance between i and $i+1$ is identified as $\Delta x_i(t)$. Also, we denote input parameters for the vehicular mobility descriptions with the following notation:

- a, b: acceleration, deceleration
- v_{min}, v_{max}: minimum, maximum (desired) speed
- Δt, time step
- Δx_{min}, minimum safety distance.

Stochastic models include all those mobility descriptions which constrain random movements of nodes on a graph.

The graph represents a road topology, and the movement is random in a sense that vehicles, individually or with group dynamics, follow casual paths over the graph, usually traveling at randomly chosen speed. Stochastic models are the simplest vehicular mobility descriptions used in vehicular networking research, as they do not consider any vehicular traffic theory result.

The City Section mobility model [1] constrains the movement of nodes on a grid graph, and limits their speed to fixed constant values depending on the edge they are traveling on. The movement patterns are determined by running a shortest path algorithm to a destination randomly selected among the vertices of the grid. An extension is provided by the Constant Speed Motion (CSM) [2] model, which also considers a pause time T_p at intersections. The Manhattan and Freeway mobility models [3], [4] add some speed management to the previous scheme, according to the following set of rules:

$v_i(t + \Delta t) = v_i(t) + \eta\ a\ \Delta t$;
IF $v_i(t) < v_{min}$ THEN $v_i(t) = v_{min}$;
IF $v_i(t) > v_{max}$ THEN $v_i(t) = v_{max}$;
IF $\Delta x_i(t) \leq \Delta x_{min}$ THEN $v_i(t) = v_{i+1}(t) - a/2$;

where η is a random variable uniformly distributed in $[-1, 1]$. These models thus add some bounded randomness in the velocity update, and from the fourth rule above, impose speed limitations to avoid overlapping of vehicles.

Traffic stream models look at vehicular mobility from a macroscopic point of view, treating it as a hydrodynamic phenomenon, and relate the three fundamental variables of velocity (measurable in km/h), density (measurable in vehicles/km), and flow (measurable in vehicles/h). These models are rarely used in network simulation, as they cannot capture a per-node behavior. However, the Fluid Traffic Model (FTM) [5] can be seen as an hybrid model, adopting a traffic stream approach on a microscopic level. As a matter of fact, FTM describes the speed as a monotonically decreasing function of the vehicular density, forcing a lower bound on speed when the traffic congestion reaches a critical state, by means of the following equation

$$v_i(t + \Delta t) = max\left[v_{min}, v_{max}\left(1 - \frac{n/l}{k_{jam}}\right)\right] \qquad (1)$$

where k_{jam} is the vehicular density for which a traffic jam is detected, n is the number of cars on the same road 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 speed value. Notice that a road can be divided into segments, in each of which the vehicular density is computed independently.

Car-following models describe the behavior of each driver in relation to the vehicle ahead. As they consider each car as an independent entity, they fall into the category of microscopic level descriptions.

In [6], the author employs a car-following model for single-lane, bi-directional straight road movement, from Krauß [7]. The model takes four input variables (v_{max}, a, b, as defined before, and the noise η that introduces stochastic behavior in the model), and is built up by the following set of equations

$$v_i^s(t + \Delta t) = v_{i+1}(t) + \frac{\Delta x_i(t) - v_{i+1}(t)\tau}{(v_i(t) + v_{i+1}(t))/2b + \tau} \qquad (2)$$

$$v_i^d(t + \Delta t) = min\left[v_{max}, v_i(t) + a\Delta t, v_i^s(t + \Delta t)\right] \qquad (3)$$

$$v_i(t + \Delta t) = max\left[0, v_i^d(t + \Delta t) - \epsilon\ a\ \Delta t\ \eta\right] \qquad (4)$$

(2) computes the speed of vehicle i required to maintain a safety distance from its leading vehicle. The reaction time of the driver is represented by the time τ. (3) determines the desired new speed of vehicle i, which is equal to the current speed plus the increment determined by the uniform acceleration, upper bounded by the maximum safe speeds. (4) determines the actual speed of the following vehicle by adding some randomness using the measure of a maximum percentage ϵ of the highest achievable speed increment $a\Delta t$ (η is a random variable uniformly distributed in $[0, 1]$). The same model is also used within the Simulation of Urban Mobility (SUMO) project [8], which is developing an open source traffic simulation package.

In [9], we proposed a vehicular mobility simulator for VANETs, called VanetMobiSim [10], which employs a car-following model from Treiber *et al.* [11] called Intelligent Driver Model (IDM). This model characterizes drivers behavior through the instantaneous acceleration of vehicles, computed through the following equations

$$\frac{dv_i(t)}{dt} = a\left[1 - \left(\frac{v_i(t)}{v_{max}}\right)^4 - \left(\frac{\delta}{\Delta x_i(t)}\right)^2\right] \qquad (5)$$

$$\delta = \Delta x_{min} + \left[v_i(t)T + \frac{v_i(t)\left(v_{i+1}(t) - v_i(t)\right)}{2\sqrt{ab}}\right] \qquad (6)$$

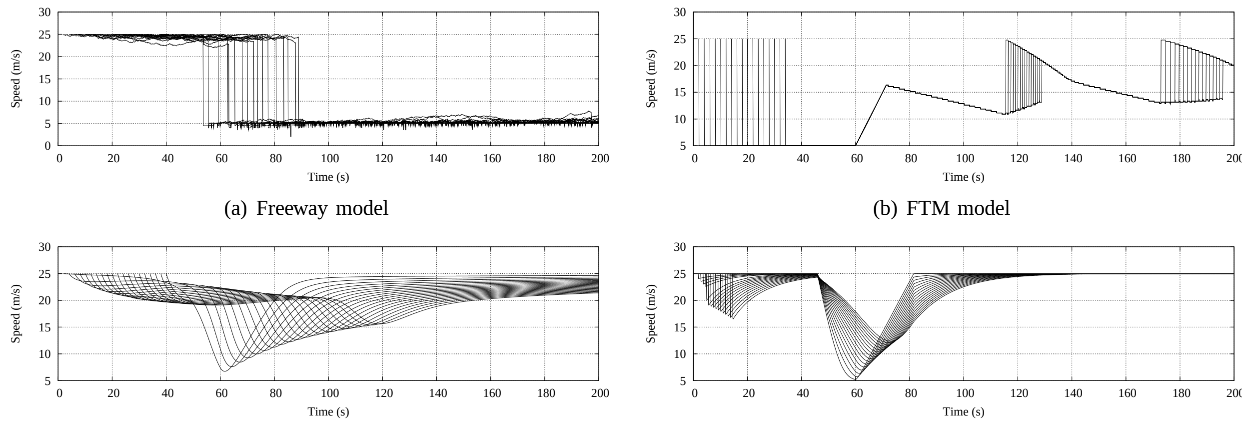
where T is the safe time headway. In (5), δ is the so called "desired dynamical distance", computed as shown in (6). The result of these formulae is the instantaneous acceleration of the car, divided into a desired acceleration $[1-(v_i(t)/v_{max})^4]$ on a free road, and a deceleration induced by the preceding vehicle $(\delta/\Delta x_i(t))^2$.

Also in [9], we introduced two extensions of the IDM model, called IDM with Intersection Management (IDM-IM) and IDM with Lane Changes (IDM-LC). Both borrow the car-to-car interaction description of the IDM model and provide intersection handling capabilities to vehicles driven by the IDM. The two models can manage crossroads regulated by both stop signs and traffic lights. The IDM-LC is also able to model lane changes according to a game theoretical approach. We refer the interested reader to the paper for a detailed description of these models. The same car-following model is adopted in [12], but without considering lane changes and intersection management.

TABLE I

MOBILITY MODELS PARAMETERS SETTING

Scenario	Model	Type	Parameters									
			v_{min} $[m/s]$	v_{max} $[m/s]$	a $[m/s^2]$	b $[m/s^2]$	T $[s]$	Δx_{min} $[m]$	τ $[s]$	ϵ	k_{max} $[car/km]$	T_p $[s]$
Highway	Freeway	stochastic	5	40	1.0	-	-	-	-	-	-	-
	FTM	traffic stream	5	40	-	-	-	-	-	-	0.1	-
	IDM	car-following	20	40	1.0	2.5	1.5	1.0	-	-	-	-
	Krauß	car-following	20	40	1.0	2.5	-	-	1.0	0.6	-	-
Urban	CSM	stochastic	5	15	-	-	-	-	-	-	-	[0,30]
	FTM	traffic stream	1	20	-	-	-	-	-	-	0.125	-
	IDM	car-following	10	15	0.6	0.9	0.5	1.0	-	-	-	-
	IDM-IM	car-following	10	15	0.6	0.9	0.5	1.0	-	-	-	-



(a) Freeway model

(b) FTM model

(c) IDM model

(d) Krauß model

Fig. 2. Evolution of speed and headway time for the first 20 vehicles belonging to a queue of cars meeting a slow vehicle ahead. At time $t = 60s$, the slow vehicle starts accelerating.

III. REALISM OF VEHICULAR MOBILITY MODELS

In order to understand the level of realism of the aforementioned models, we tested their capability to reproduce well known traffic phenomena. We consider two environments for our tests. In a highway one, we can verify how the mobility models react to controlled stimuli and thus their realism in terms of vehicle-to-vehicle interactions. In an urban scenario, we can study the behavior of the mobility models in presence of a complex road infrastructure where cars movements are constrained by rules in presence of intersections. In both cases, we analyze at least one representative model for each of the typologies discussed above, according to the scheme and parameters depicted in Table I. Due to space limitations, we cannot provide a in-depth discussion of the models calibration, and invite the interested reader to refer to the models' references for details. We just stress out that the selected parameters fit real-world values and that we calibrated them according to the respective scenarios (e.g., higher speed, acceleration and safe time headway in the highway case than in the urban scenario).

Firstly, we tested the reaction of the models to a mild perturbation. We recorded the behavior of a flow of cars traveling on a single-lane road and encountering a slow vehicle ahead. A real-world behavior would force the vehicles to slow down (each with different dynamics, as the first vehicle brakes the hardest, while the following experience progressively smoother decelerations) and form a queue when the obstacle becomes visible. Then, as the obstacle is removed, cars start accelerating again, and propagate the speed increase through the queue. This is what can be observed in Fig. 2, at least for the IDM and Krauß models (even though on different time spans, because of the differences in the models' settings). On the other hand, when following the Freeway 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, with the addition of the rule

$$\text{IF } v_i(t) > v_{i+1}(t) \text{ THEN } v_i(t) = v_{i+1}(t);$$

in order to prevent vehicles from overtaking the obstacle, only generates a very rough reproduction of the correct behavior. We can notice from Fig. 2(b) that vehicles abruptly stop one after the other (vertical lines in the first part of the plot) in presence of the obstacle. Once the impediment is removed, all vehicles begin a growing speed evolution, with periodic

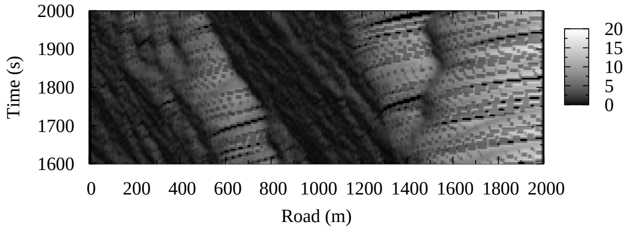


Fig. 3. Speed waves generated by the IDM model in presence of severe traffic congestions on the highway scenario.

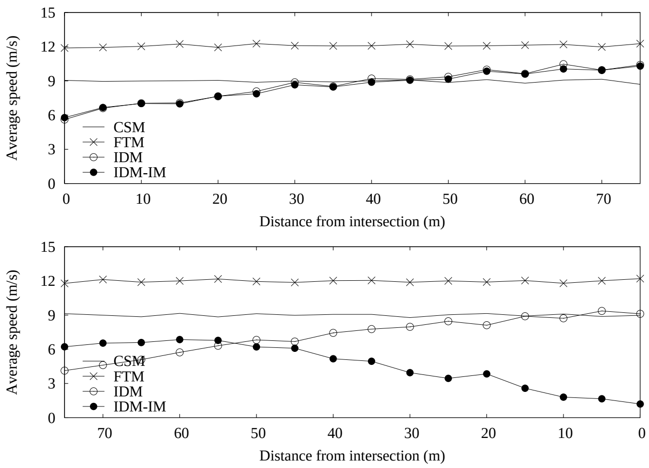


Fig. 4. Average speed profile of vehicular out-flow (top figure) and in-flow (bottom figure) in presence of an intersection.

speed increment and decrements, due to the movement of cars between subsequent road slots where the vehicular density is computed independently.

Traffic congestion is also known to produce typical slow-speed waves, which move backwards with respect to the direction of vehicular motion as time progresses. In Fig. 3, we were able to recreate this effect using the IDM model, and got a slightly less accurate result with the Krauß models. The FTM and Freeway models however failed to generate this phenomenon.

We finally tested the accuracy of different typologies of models in presence of an intersection. Since this can be considered as the basic building block for any city road topology, the urban scenario models were employed for those tests (see Table I). Fig. 4 shows the average speed of vehicles leaving and approaching the intersection obtained with different mobility models. The stochastic (CSM) and traffic stream (FTM) models completely ignore the intersection and produce constant speed curves in both cases. The IDM correctly reproduces the behavior of cars leaving the intersection with a constant acceleration, but it is far from reality in the in-flow case, as the speed *increases* as we get nearer to the crossroads. The reason is that IDM neglects flows on the intersection roads as well, and vehicles travel as in presence of free road. The IDM-IM model, here used together with a traffic light model, is the only description to generate realistic curves, with a

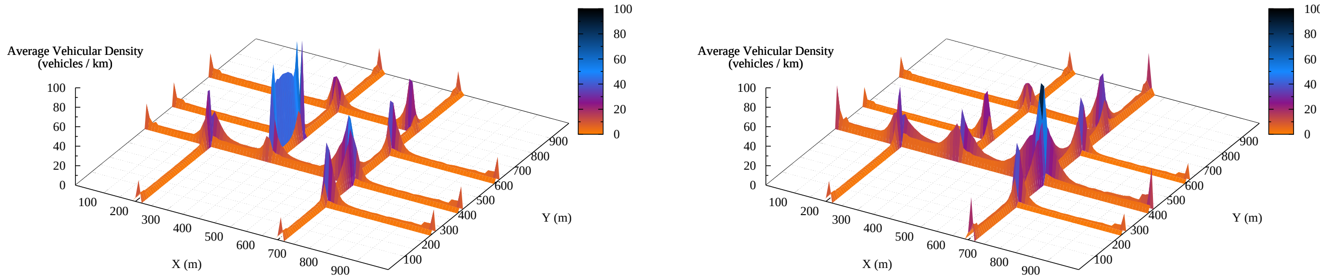
TABLE II
SIMULATION PARAMETERS SETTING

Network Simulator	ns-2 2.29
Simulation duration	23 runs of 100s each
Simulation area	1000 x 1000 m^2
Number of vehicles	200
Propagation model	Shadowing model (α 3.3dB, σ_ϵ 1.0)
Transmission rate	Rate adaptation based on AARF
Transmission range	200m at 1Mbps
MAC Protocol	IEEE 802.11 DCF
Routing protocol	DYMO ($Hello^{dymo}$ interval 1s)
Data traffic	single s/d pair, CBR at 5kbps

progressive deceleration as soon as the intersection has come into driver's sight.

These tests clearly showed that car-following models are able to accurately represent real world vehicular traffic dynamics on a straight road scenario, whereas models involving lower levels of detail fail to describe the same conditions, mainly because of an insufficient description of the car-to-car interaction when determining vehicles behavior. We also proved that car-following models, in turn, fall short from the goal of realism when flows on different roads have to interact. This is the case of intersections, where an ad-hoc management is required in order to obtain faithful reproduction of the real-world behavior of vehicle mobility. Further proofs of the realism of the IDM-IM model has been obtained by the fact that it is has been recently validated against a well known commercial traffic simulator.

A final aspect, which has to be considered to achieve a complete realism in modeling vehicular mobility in an urban environment, involves activity planning, i.e. the way cars choose their destinations and the routes to reach them. The standard approach in vehicular networking literature is to randomly pick destinations and then use a shortest path algorithm to compute the route to them. In fact, this can lead to very unpredictable behaviors. As an example, we show in Fig. 5 the average vehicular density in a city section obtained with the IDM-IM model. Intersections are regulated by traffic lights and two different activity planning strategies are used. In Fig. 5(a), we used the random technique described before, while in Fig. 5(b), we used an activity matrix to regulate the transitions between different sets of origin/destination points, and a route selection algorithm that weights streets speed limits in the path cost computation. In the former case, the lack of realistic activity planning brings to a very heavy traffic on one slow and short road section that belongs to most of the shortest paths of the road topology. This behavior has a limited chance to occur in the real world. On the other hand, when an activity planning is considered, vehicles tend to choose the fast and possibly longer roads of the topology. Accordingly, most traffic is found on the main intersections, while the short and minor roads are not overloaded and no traffic jam is encountered. It is clear that the second solution models more realistically vehicles movement in the urban environment under study.



(a) random mobility

(b) activity-based mobility

Fig. 5. Vehicular density in an urban scenario obtained with the IDM-IM model.

IV. Effect of mobility on networking metrics

The obvious question at this point is: given the proved superior realism of some vehicular mobility models over the others, does using such realistic models instead of a simpler ones really affect network simulations ?

In order to answer, we simulated vehicular mobility in a city section and examined the impact of the different urban scenario models (plus the Random Waypoint Model (RWM), included as a benchmark) on the performance of an ad-hoc routing protocol. The meaningful simulation settings[1] are reported in Table II, whereas the models settings are again those in Table I.

Our analysis is twofold. First, we perform a spatial analysis and illustrate the diversity behind the variance on the spatial domain. Secondly, we move to a temporal analysis in order to depict diversities in the time domain. Note that we chose to avoid a mean-value study, where results are averaged over space and time for each scenario. Although being the standard procedure in the vehicular networking performance evaluation literature, this approach does not lead to a sufficiently deep analysis. It indeed neglects the nature of vehicular mobility, which never reaches a stationary state, but continuously evolves over time and space.

We considered two significant metrics for MANETs routing that are mostly influenced by mobility:

- *Packet Delivery Ratio (PDR)* – the ratio between the number of packets delivered to the receiver and the number of packets sent by the source.
- *Hop Count* – the number of hops over relay nodes that a packet undergoes before being correctly delivered to the destination.

In the spatial analysis, we are want to observe the evolution of routing metrics as a function of the number of hops[2].

In a mean-value analysis, the Hop Count resulted to be on average the same for all mobility models, a fact which could misleads us to conclude that mobility models do not affect network metrics. We can instead see in Fig. 7 that such a conclusion would be wrong. The figure depicts the PDR as a function of the Hop Count, averaged over 23 simulation runs, and shows an evident diversity of shapes: the resulting average value might yet be similar, but the distribution of the PDR over the Hop Count changes significantly with the different mobility models. And it is precisely this diversity that reflects the intrinsic characteristics of the different mobility models in a way that cannot be shown by a mean-value analysis.

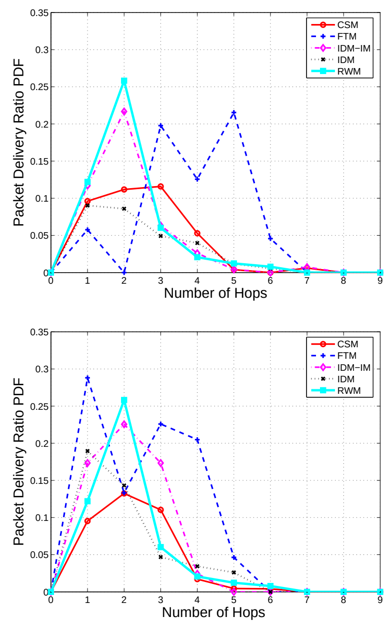
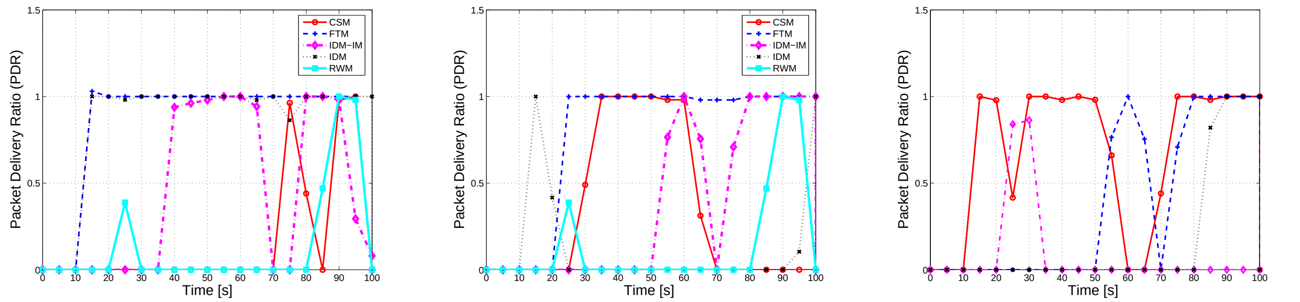


Fig. 7. PDR distribution over Hop Count, with random mobility (top figure) and activity-based mobility (bottom figure).

As an example, the FTM model with random trips has a strong multi-hop behavior, an effect that comes from a more uniform distribution of cars than in other scenarios. However, when we look at the activity-based case, this multi-hop behavior is reduced, as strong accumulation points are generated in urban bottlenecks. Similarly, the IDM-IM scenario has a multi-hop behavior similar to RWM for the random trip case, but comes much closer to the FLUID scenario for activity-based trips. Finally, all scenarios have better multi-hop characteristics

[1]In the rest of the paper, we will dub a source/destination pair as a *s/d pair*.

[2]Although not being a very precise way to evaluate the distance between a s/d pair, the Hop Count provides an estimate of the length of the path between them.



(a) Single s/d pair, random mobility

(b) Single s/d pair, activity-based mobility

(c) Multiple s/d pairs, activity-based mobility, IDM-IM model

Fig. 6. PDR versus time, for different configurations

than the RWM, although RWM maintains a more uniform distribution of nodes. Again, one of the justification behind this effect is the difference between having a *sampled* uniform distribution, and moving in *similar patterns*.

In the spatial analysis, we managed to depict the intrinsic characteristic of different mobility scenarios. However, it is not possible to directly observe the different mobility patterns followed by nodes, as this also depends of another aspect: time.

In Fig. 6(a) or Fig. 6(b), we randomly chose a s/d pair and depicted the evolution over time of the related PDR when different mobility models are employed. Similar conclusions can be reached from the analysis on the delay and hop count. Indeed, the FTM model shows a stable path unlike most of the other models, a behavior that is maintained also in activity-based trips. And by comparing those results with Fig. 7, FTM seems able to maintain more stable multi-hop paths than other models.

Fig. 6(a) and Fig. 6(b) also depict the drastic effects of vehicular mobility during time, as models are subject to peaks of PDR at some time instants, whereas the rest of the time no path may be established. It is an *all-or-nothing* situation, where packets may only be routed with high probability at some particular time instants at which the patterns are beneficial to the s/d pair communication. This pattern is usually called the *encounter* mobility pattern, a frequent pattern in urban environments. Indeed, due to the high dynamics of urban mobility models, a path cannot be kept for long, but nodes are expected to meet in accumulation points, such as intersections or on preferred paths, where the network configuration reaches a good PDR for short time instants. In order to show that this effect does not depend of the choice of the s/d pair, we provide in Fig. 6(c) the evolution with time of the PDR for different s/d pairs. Although there is a large variance of the PDR, the *peak* effect can be clearly observed in all the curves.

Concluding, we can state that different mobility models have a noticeable impact on networking metrics, and since some models proved to be more realistic than others during the extensive tests conducted in Section III, they should be used to produce reliable results.

V. Conclusions

In this paper, we discussed different vehicular mobility models in terms of their analytical description and verified their realism, in both highway and urban scenarios, by testing their capability to reproduce well known phenomena of vehicular traffic. We then verified the impact that mobility models have on the performance of a network routing protocol, showing that diverse descriptions produce different results in the spatial domain (as a function of the hop count) and in the temporal domain (as a function of time). Based on this study, it is our advice that only realistic models, such as car-following models with intersection management capabilities, be used for simulation studies of vehicular networks.

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