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Analysis of Vehicular Mobility Patterns on Routing Protocols

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Abstract

In this report, we illustrate how the realistic motion patterns introduced VanetMobiSim [1] affect the velocity, and how new parameters become necessary to evaluate the performance of routing protocols in Vehicular Ad Hoc Networks (VANETs). To express our point, we evaluate the performance of AODV with realistic urban scenarios. We show how new urban specific parameters have significant impacts on routing, and de-facto replace some non-urban specific parameters. For example, the average velocity appears to be irrelevant in urban scenarios and should be replaced by road segment lengths. Then, we evaluate AODV and OLSR performance in realistic urban scenarios. We study those protocols under urban-specific metrics such as road segment length, and cluster effect, or non-urban specific metrics such as vehicle density, and data traffic rates. We show that clustering effects created by cars aggregating at intersections have remarkable impacts on evaluation and performance metrics. We conclude that OLSR is a better candidate than AODV for routing in VANET in urban areas.

Index Terms

Simulation Parameters, Performance Evaluation, Urban Environment, Realistic Vehicular Mobility Models, AODV, OLSR, VANET.

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1 Introduction

One of the critical aspects when evaluating routing protocols for VANETs is the employment of mobility models that reflect as closely as possible the real behavior of vehicular traffic. Simple random models cannot describe vehicular mobility in a realistic way, since they ignore the peculiar aspects of vehicular traffic, such as cars acceleration and deceleration in presence of nearby vehicles, queuing at roads intersections or traffic bursts caused by traffic lights. All these situations greatly affect the network performance, since they act on network connectivity, which makes vehicular specific performance evaluations fundamental when studying routing protocols for VANETs. Initial works [2, 3] on performance evaluation were based only on random motions, such as random walk models, and lacked any interaction between cars, generally referred as *micro-mobility*. Following the recent interest in realistic mobility models for VANETs, new studies appeared on performance evaluations of VANETs in urban traffic or highway traffic conditions [4, 5]. As these new models generates urban specific spatial and temporal dependencies, the real mobility parameters differ from the initial and controlled ones. Performance comparison may become unfair and arguable.

Another critical aspect is to use the appropriate parameters in order to evaluate routing protocols. A crucial parameter influencing the performance of Vanets is referred by the generic term *mobility*. In simple models, mobility is equal to velocity. However, on the eve of realistic mobility models, it becomes hard to understand the real parameters controlling this *mobility*. However, only few studies have been done illustrating how realistic motion patterns influence the mobility and other configuration parameters.

Our objective is to illustrate how realistic urban motions reduce the effect of some standard evaluation metrics, and how they generate new urban-specific performance parameters never described in the past. Using VanetMobiSim Model (VMM) presented in [1], it becomes possible to evaluate more realistically ad hoc routing performances for vehicular networks. We configure VanetMobiSim to model an urban environment, then evaluate the performance of AODV and OLSR in terms of *(i) Packet Delivery Ratio (PDR) (ii) Delay (iii) Hop Count*. We test AODV and OLSR in four different conditions *(i) velocity (ii) road segment length (iii) cluster effect (iv) traffic load*.

We first show how the average velocity has a minor impact on performance as it cannot reflect the real velocity in urban traffic. A more significant parameter is the road segment length, as this is the parameter controlling the real velocity. We also exhibit how the clustering effect obtained at intersection has a major effect on the effective average velocity during the simulation. We finally illustrate how OLSR outperforms AODV and is consequently a better candidate than AODV for routing in urban environment.

The rest of the Report is organized as follows. In Section 2, we provide a brief overview of related work in MANET protocol evaluation and comparison. Section 3 illustrates the effects of VMM mobility patterns on standard performance parameters. In Section 4, we evaluate AODV and OLSR performance in realistic urban scenarios, and finally we provides conclusions in Section 5.

2 Related Work on MANET Protocol Comparison

Several studies have been published comparing the performance of routing protocols using different mobility models or performance metrics. One of the first comprehensive studies was done within the framework of the Monarch project [2]. This study compared AODV, DSDV, DSR and TORA and introduced some standard metrics that have been then used in further studies of wireless routing protocols. A paper by Das et al. [3] compared a larger number of protocols. However, link level details and MAC interference are not modeled. Another study [6] compared the same protocols as the work by Broch et al. [2], yet for specific scenarios as the authors understood that random mobility would not correctly model realistic network behaviors, and consequently the performance of the protocols tested. Globally, all these papers concluded that reactive routing protocols perform better than proactive routing protocols.

Although the proactive OLSR protocol has been developed in 2002, very few studies compared it with other ad hoc network protocols. Clausen *et al.* [7] evaluated AODV, DSR and OLSR in varying network conditions (node mobility, network density) and with varying traffic conditions (TCP, UDP). They showed that unlike previous studies, OLSR performs comparatively to the reactive protocols.

Following the developments started with scenario-based testing, it also became obvious that, as scenarios were able to alter protocol performances, so would realistic node-to-node or node-to-environment correlations. This approach became recently more exciting as VANETs attracted more attention, and a new wave of vehicle-specific models appeared. The most comprehensive studies have been performed within the Fleetnet project [8]. In a first study [4], authors compared AODV, DSR, FSR and TORA on highway scenarios, while [5] compared the same protocols in city traffic scenarios. For instance, they found that AODV and FSR are the two best suited protocols, and that TORA or DSR are completely unsuitable for VANET. Another study [9] compared a position-based routing protocol (LORA) with the two non-position-based protocols AODV and DSR. Their conclusions were that, although AODV and DSR perform almost equally well under vehicular mobility, the location-based routing schema provides excellent performance. Similar results has been reached by members of the NoW project [10], which was their major justification for the design of position-based forwarding techniques. However, to the best of our knowledge, no performance evaluation has been conducted between OLSR and other routing protocols under realistic urban traffic configurations.

3 Influence of VanetMobiSim on Vehicular Motion Patterns

The VanetMobility Model (VMM) requires many configuration parameters, all of which have effects on the modeling of vehicular motions. In this section, we illustrate the average *road segment length*, the average *acceleration, resp. deceleration rate*, and the *clustering effect*, which are three major novel motion parameters VMM defines, and compare their influence on the RWM.

With these parameters, VMM generates motion patterns that cannot be modeled by pure random motions. Yet, these parameters deeply influence the spatial distribution and velocity of cars in the network. Indeed, any single one or any combination of them is able to generate a significant difference between the initial average velocity and the real velocity, or between the average and the local density. This problem may be formulated as the difference between initial distribution of the statistics of mobility parameters and the steady state distribution. However, as the problem of computing analytically the steady state distributions of realistic mobility models is much more complex than that of random models, the only way to illustrate this effect is through simulations. The corollary is that any simulation must be undertaken after a sufficiently large "warming" time in order to reduce the effect of the transient state.

3.1 Parameters Definition

Before going further, we would like to define the particular parameters we use in this Chapter.

We first provide *Speed* related definitions

- *Average Speed*– The average speed controls the distribution of the random variable that determines the speed between each destination point.
- *Desired Speed*– The desired speed is the speed sampled at each destination point. It is therefore the speed a driver aims at reaching using a smooth acceleration. However, according to traffic regulations, there is no guarantee that this speed may ever be reached.
- *Real Speed*– The real speed is the temporal speed obtained at each time instant. It is subject to traffic, traffic signs and driver habits.
- *Speed Decay*– The speed decay is the gap between the desired speed and the real speed.

Then, the *Clustering Effect* is a particular parameter specific to realistic mobility models which should not be mistaken with the *density* or the *number of nodes*. Indeed, the clustering effect is a parameter taken from urban traffic modeling and controls the aggregation at the intersections. Our purpose is to spot out the effects solely dependent on the urban traffic distribution and not dependent on effects on the MAC layer or on routing protocols from an increased number of neighbors. Accordingly, the clustering effect is controlled by increasing the number of vehicles in the urban area, while reducing the transmission range in order keep the average network density constant[1] (in terms of average number of neighbors per vehicle). Thanks to it, we are able to see the effect of spatial and temporal dependencies on routing protocols, and not only the effect of the density that has already been studied in the past.

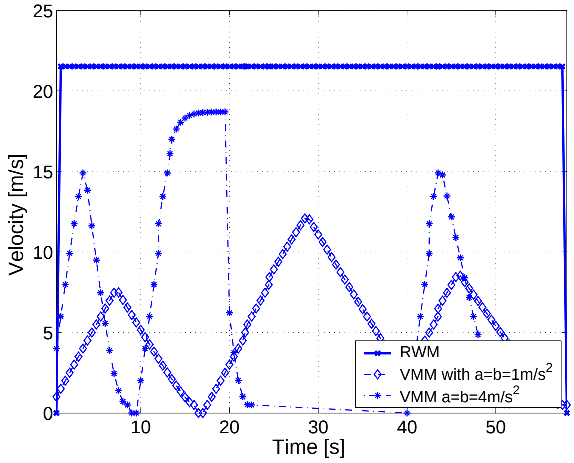
Finally, a *Road Segment* is defined as the piece of road connecting two intersections. The length of a road segment is therefore the distance between two intersections. Its major effect on realistic mobility models is its control of the gap between the desired speed and the real speed. It is also able to control the clustering effect.

3.2 Illustration

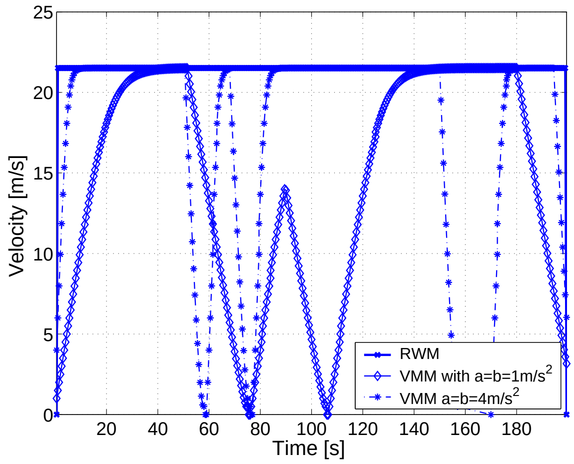
In Fig. 1, we illustrate the effects of the average road segment length and the acceleration, resp. deceleration rate, on the real velocities of vehicles. In both figures, the desired velocity is the one reached at any time by RWM, and we modeled the velocity of a single vehicle during on single trip. Unlike the RWM which ignores the VMM's parameters, the velocity modeled by VMM fluctuates significantly as it is influenced by the acceleration rate and the road segment length. By considering the acceleration rate $1m/s^2$ and comparing Fig. 1(a) and 1(b), vehicles never reach the desired speed in the former figure, as cars modeled by VMM respect traffic regulations and must decelerate and stop at each intersection in the trip. However, the effect may be limited by increasing the distance between two successive intersections as it can be seen in the latter figure. The second parameter is the acceleration, resp. deceleration rate. Considering Fig. 1(a), for a fixed distance between two intersections, a car with a strong acceleration rate is quickly going to reach the desired speed and will run faster on the selected road segment than a car with a smaller acceleration rate. Since the real velocity is an important parameter for routing protocols in mobile ad hoc networks, we expect these new parameters to be more fundamental than average, or desired velocities.

RWM's objective is to keep vehicles position uniformly distributed in the network, an effect that may be sought for SANETs for instance. However, for VANETs, this is seldom the case as vehicles follow predefined paths and aggregate at intersections. This leads to a non-uniform distribution of vehicles in the network, which we call the *clustering effect*. As we see on Fig 2(b), the number of vehicles observed in the network is higher on predefined roads and even higher on intersections, while the number of vehicles is, as expected, uniformly distributed in Fig 2(a). Since the distribution of vehicles in the network has an impact on connectivity and data dissemination, we also expect the clustering effect to have a

[1] It is possible to obtain a significant performance difference if we have a large clustering effect at a low network density or a low clustering effect at a high network density.



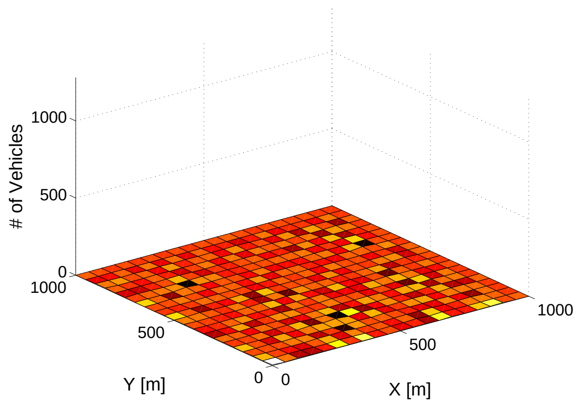
(a) Road segment length=150m



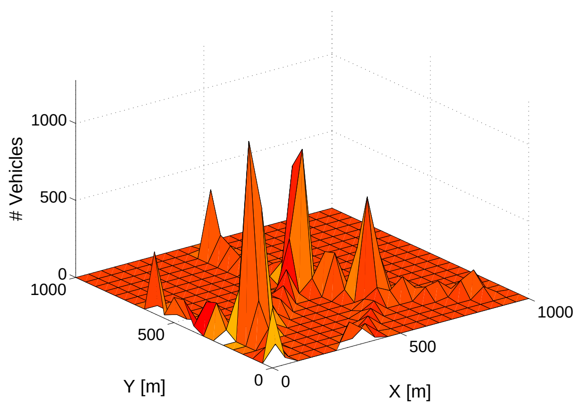
(b) Road segment length=250m

Figure 1: Illustration of vehicular real velocity on a single trip, where a and b are the acceleration, resp. deceleration rate

signifi cant influence on performance of mobile ad hoc networks in vehicular urban areas.



(a) RWM



(b) VMM

Figure 2: Spatial distribution of vehicles in the urban environment (Cluster Effect)

As an illustration of a possible effect on performance, we show in Fig. 3 the average speed decay from a desired velocity that vehicles experience with VMM. However, this desired velocity is subject to speed limitations that cannot be exceeded, or to any obstacle that either reduces the vehicle speed or even forces it to stop. Accordingly, there is no guarantee that this velocity can even be reached during the simulation. As we can see on Fig. 3(a), there is drastic decay as a function of the desired velocity, whereas the decay is not stable in Fig. 3(b), since it is influenced by the road segment length or acceleration, resp. deceleration rates.

The main conclusion is that network mobility as defined in previous works cannot be used as an evaluation metric for vehicular ad hoc networks. We should rather define new metrics as acceleration/deceleration factors, clustering effect or distance between two intersections.

4 Performance Evaluation

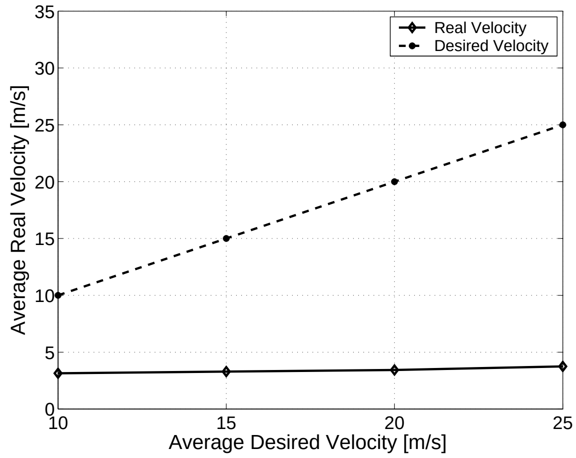
In order to illustrate the influence of the new parameters described in the previous section on routing protocols, we used the open source network simulator ns-2 in its version 2.27 as it is widely used for research in mobile ad hoc networks. We first provide a description of the scenarios and then present the obtained results.

4.1 Scenario Characteristics

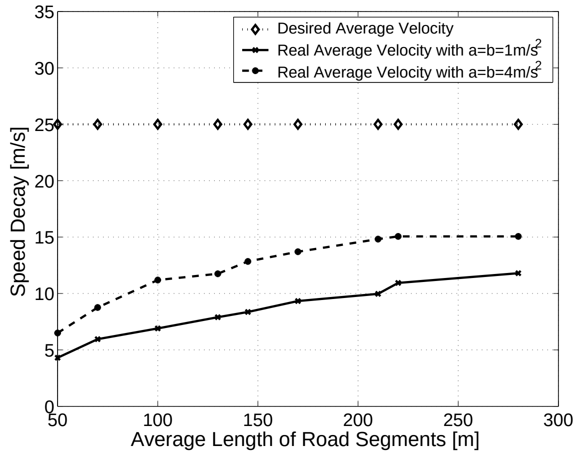
In this Chapter, we consider squared urban areas of 1000x1000m constituted of three different cluster categories: downtown, residential and suburban. The different obstacle densities for these three categories are summarized in Table 2(b). Fig. 4 displays an example of an urban graph used in this Chapter. The simulation parameters are given in Table 1. We test each protocol with a spatial model composed of 30% of traffic lights and 70% of stop signs.

Vehicles are randomly positioned on intersections. Then, each vehicle samples a desired speed and a target destination. After that, it computes the shortest path to reach it, taking into account single flow roads. Eventually, the vehicle moves and accelerates to reach a desired velocity according to street regulations. When a car moves near other vehicles, it decelerates to avoid the impact. When it is approaching an intersection, it first acquires the state of the traffic sign. If it is a stop sign or if the light is red, it decelerates and stops. If it is a green traffic light, it slightly reduces its speed and proceeds to the intersection. At target destination, the car decelerates, stops, and then samples a new destination. The different parameters for the micro-model are given in Table 2(a).

We finally decompose our performance analysis in three different scenarios, where parameters are fixed according to Table 4. In the first scenario, we want to see the influence of the average velocity. Next, we analyze the effect of different lengths of road segments. In the last scenario, we are interested in the clustering effect at intersections. Each point is the average of 10 samples, while the error bars represent a 95% confidence interval. We also point out that in all three scenarios, we maintain the same average density, as we want to exhibit results not related to an increased density. Finally, for each scenario, we simulate AODV for the RWM [11] and the VMM. Accordingly, we are able to see the effect of realistic urban motions on the parameters and on the performances.



(a) Average Desired velocity



(b) Average length of road segments

Figure 3: Illustration of Speed Decay, where a, resp. b are the acceleration, resp. deceleration rates

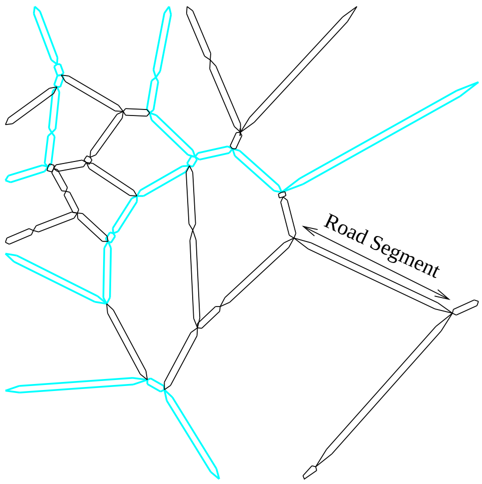


Figure 4: Illustration of an urban graph used for the simulations

Network Simulator	ns-2 2.27
Mobility Models	RWM [11], VanetMobiSim [1]
AODV Implementation	AODV-UU
$Hello^{aodv}$ Interval	3s
OLSR Implementation	UM-OLSR
$Hello^{olsr}$ Interval	0.5s
TC^{olsr} Interval	2s
Simulation time	1000s
Simulation Area	1000m x 1000m grid
Number of Nodes	$10 \rightarrow 80$
Tx Range	100m
Speed	Uniform
Density	$\#nodes \cdot \frac{\pi \cdot range^2}{X_{dim} \cdot Y_{dim}}$
Data Type	CBR
Data Packet Size	512 bytes
MAC Protocol	IEEE 802.11 DCF
MAC Rate	2 Mbits/s
Confi dence Interval	95%

Table 1: Simulation parameters

Param	Description	Value
a	Maximum Acceleration	$0.9m/s^2$
b	Maximum Deceleration	$0.5m/s^2$
l	Vehicle Length	5m
s_{com}	Minimum Congestion Distance	2m
t	Safe headway time	1.5s
b_{sav}	Maximum ”safe” deceleration	$4m/s^2$
p	Politeness	0.5
a^{th}	Lane Change Threshold	$0.2m/s^2$
T^{light}	Traffi c Light Transition	30s

(a) Micro-model

Clusters	#obstacles per $100m^2$	#cluster per $1000m^2$	ratio
Downtown	50	4	10%
Residential	12.5	4	40%
Suburban	2.5	4	50%

(b) Macro-model

Table 3: Vehicular Mobility Model parameters

Scenarios	Data Rate [Mbits/s]	Network Mobility [m/s]	Nodes Density	Road Length [m]	Nbr. of Nodes	Tx Range [m]
Velocity	0.8	v^{min}=0, v^{max}=20 to v^{min}=15, v^{max}=35	11.78	50	40	100
Road Segment Length	0.8	v^{min}=15, v^{max}=35	11.78	50 to 280	40	100 to 500
Clustering Effect	0.8	v^{min}=15, v^{max}=35	11.78	150	20 to 60	424 to 244
Data Rate	0.02 to 8	v^{min}=15, v^{max}=35	11.78	50	60	100
Network Density	0.8	v^{min}=15, v^{max}=35	1.96 to 15.7	50	10 to 80	100

Table 4: Simulation Scenarios

4.2 Metrics Definitions

We measured several metrics for MANETs routing that are mostly influenced my mobility:

- *Packet Delivery Ratio (PDR)*– It is the ratio between the number of packets delivered to the receiver and the number of packets sent by the source.
- *Delay*– It measures the average end-to-end transmission delay by taking into account only the packets correctly received.
- *Hop Count*– It represents the number of hops that a packet has taken before it has been correctly delivered.

4.3 Influence of Vehicular Mobility Patterns on AODV

In Fig. 5(a), we see that for VMM[2], the average velocity does not have any effect on the PDR, which is a surprising result since the velocity is a common metric in performance evaluation, and previous results have shown that AODV was sensitive to it. On the other hand, the performances with RWM are influenced by the velocity and differ signifi cantly from those with VMM. Indeed, we see in

[2]In the remainder of this Chapter, we will refer only to the mobility model for actually mentioning AODV using the mobility model

Fig. 5(b) that an increasing velocity worsens the delay for the RWM, but does not significantly impact the VMM. Similarly, Fig. 5(c) illustrates how a higher velocity reduces the number of hops for VMM, but does not conclusively affect RWM.

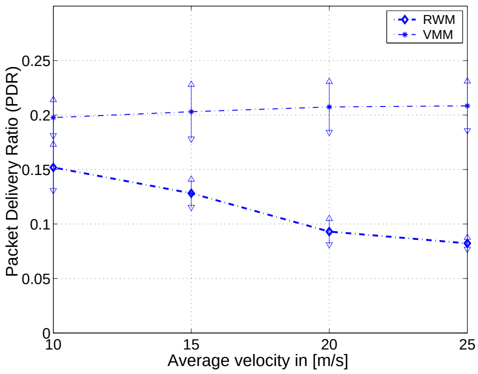
Actually, the explanation for this behavior comes from the micro-model and its interaction with the spatial environment. Indeed, when modeling smooth transitions and realistic interactions with urban traffic regulations, a fixed initial velocity does not make any sense. Instead, we define an *average desired velocity* a driver aims at reaching with a smooth acceleration. However, this desired velocity is subject to speed limitations that cannot be exceeded, or subject to obstacles that reduces vehicle speed or even forces it to stop. Accordingly, there is no guarantee that this velocity can even be reached during the simulation. And, as it can be seen in Fig. 3(a), the real speed is stable with respect to the average velocity, and significantly lower than the desired velocity, which explains the relative stability of AODV with VMM.

In the next set of simulations, we illustrate the effect of the average length of road segments on the performance of AODV. By increasing the length of road segments from 50m to 300m, we actually model urban traffic distribution observed from small roads in highly urban areas to highways in major commuting corridors. By fixing the average desired velocity and increasing the road length, we increase the time spent by vehicles on the road elements, which in turn reduces the clustering effect and also increases the chance to reach the desired speed. In order to see the sole effect of the length of road segments and not network disconnections, we maintain a fixed node density and increase the transmission range accordingly.

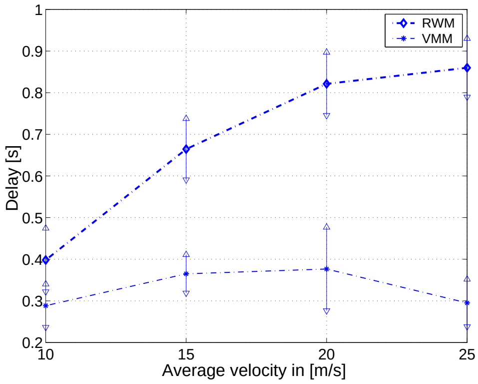
We illustrate in Fig. 6(a) how a longer road segment impacts AODV's PDR. As we could expect, RWM is not influenced by longer road segments. However, AODV's PDR with VMM is significantly improved. Fig. 6(b) and Fig. 6(c), shows that the length of road segments also influences the delay and the number of hops of AODV. Not only can we see that the average segment length has an effect on the performance of AODV, but also that the difference between VMM and RWM is not negligible. As VMM models more realistic motion patterns than RWM, we expect the performances in Fig. 6 for VMM to be closer to reality. Consequently, the length of road segments in urban scenarios should not be neglected.

We further carry on the analysis of urban traffic distribution and its effects on AODV. In the following set of figures, we increase the number of vehicles in the urban area, while reducing the transmission range in order keep the average network density constant (in terms of average number of neighbors per vehicles). We indeed want to spot out results solely dependent on the urban traffic distribution and not on effects on the MAC layer or on routing protocols from an increased number of neighbors. The average road length in this set of figures is set to 150m. By increasing the number of vehicles and keeping fixed the average road length, we actually increase the interaction of each car with its environment, which in turn limits its ability to reach a desired speed.

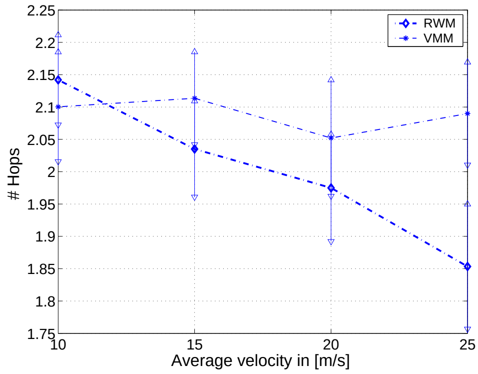
In Fig. 7(a), we depict the effect of traffic clusters at intersections, a parameter that does not influence RWM. The PDR is reduced, since it has an impact on the



(a) Packet Delivery Ratio (PDR)

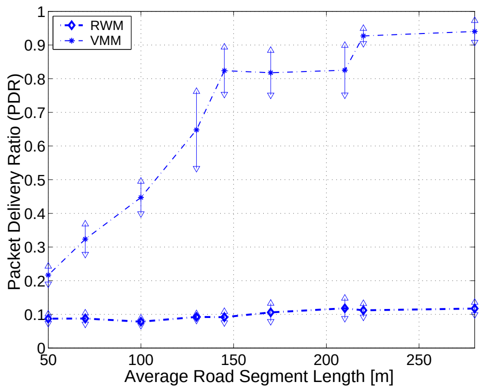


(b) End-to-end delay

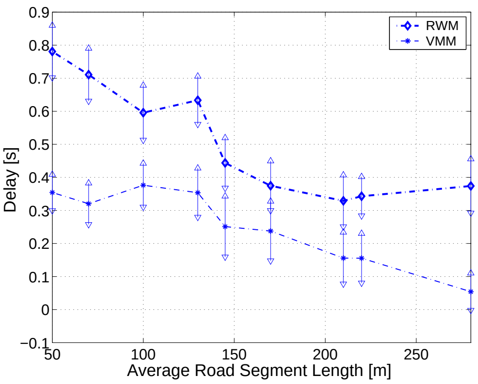


(c) Number of hops

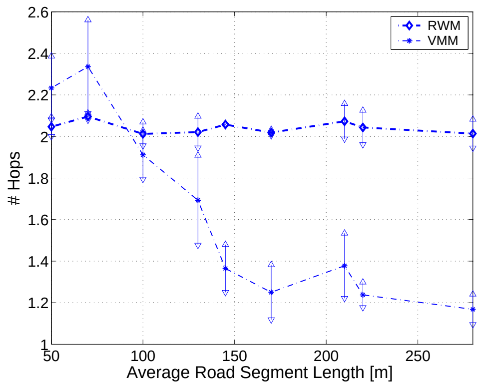
Figure 5: Performance evaluation of AODV as a function of the average desired speed



(a) Packet Delivery Ratio (PDR)



(b) End-to-end delay



(c) Number of hops

Figure 6: Performance evaluation of AODV as a function of the average length of the roads segments

spatial distribution of the vehicles. This observation is corroborated by looking at Fig. 7(b), where we see the increasing end-to-end delay, and at Fig. 7(c), where the hop count is reduced as the network is only able to deliver data to vehicles in nearby clusters. Again, besides the influence of the parameters on the performances, we see a major performance gap between VMM and RWM. We therefore illustrate how this new parameter is also able to control the performance of AODV for realistic mobility patterns in a way that is not possible by standard parameters.

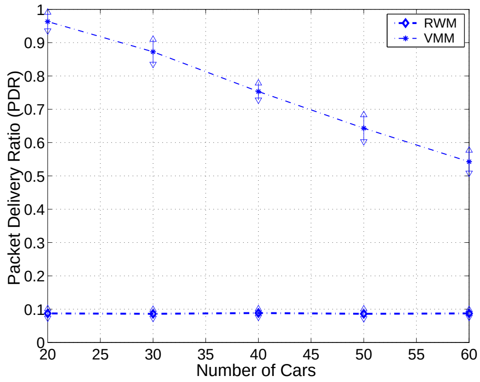
4.4 Performance Comparison between AODV and OLSR under Vehicular Mobility Patterns

In the previous section, we illustrated how realistic vehicular mobility patterns had a non negligible impact on AODV, as its performance was significantly improved. We can extrapolate that OLSR could also have different performance results under vehicular mobility patterns. We are now therefore interested in conducting a full scale performance evaluation of AODV and OLSR in order to see how they behave and see if conclusions reached in previous studies are still valid.

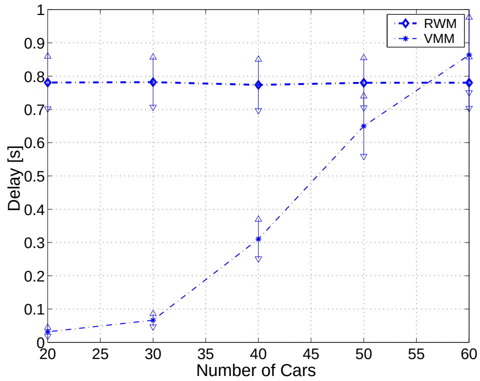
We decompose our performance analysis in four different scenarios, where parameters are fixed according to Table 4. In the first scenario, we want to see the influence of the average length of road segments. Then, in the second scenario, we analyze the clustering effect at intersections, while in the third scenario, we are interested in the data traffic rate. Finally, in the last scenario, the objective aims at observing the effect of the network density. Each point is the average of 10 samples, while the error bars represent a 95% confidence interval.

We illustrate, on the first set of simulations, the effect of the average road element length on the performance of AODV and OLSR. By increasing the length of road segments from 50m to 300m, we actually model urban traffic distribution observed from small roads in highly urban areas, to highways in major commuting corridors. By fixing the average desired velocity and increasing the road length, we increase the time spent by vehicles on the road elements, which in turn reduces the clustering effect and also increases the chance to reach the desired speed. In order to see the sole effect of road segment length and not network disconnections, we maintain a fixed node density and we increase the transmission range accordingly.

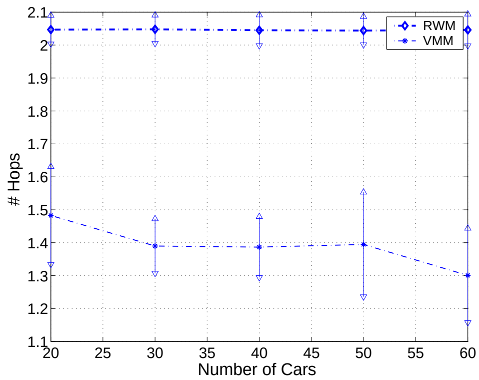
On Fig. 8(a), we see that OLSR PDR is less sensitive to the road length than AODV's. As we decrease the length of road segments, the distribution of vehicles on the simulation area becomes more and more clustered on intersections, and AODV is more dependent to this effect than OLSR. On Fig. 8(b), AODV's control packets drop as the length of road elements increases. AODV RO ends up being 75% lower than OLSR. As we see, OLSR control traffic may be assumed to be independent of the road length, as it is only dependent to network density or velocity. Moreover, the increase in the average speed is too limited to have a direct impact on it. On the other hand, the improved spatial distribution has a major impact on AODV as it improves the dissemination of buffered active routes at intermediate nodes, which in turn reduces the number of control packets required to open a route



(a) Packet Delivery Ratio (PDR)



(b) End-to-end delay



(c) Number of hops

Figure 7: Performance evaluation of AODV as a function of the number of vehicles (cluster effect)

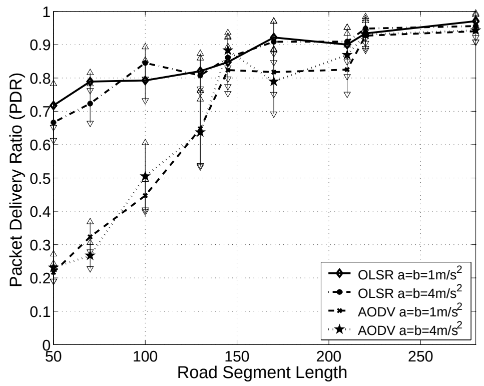
to a destination vehicle. And as we reduce the amount of control packets to open a route, the delay can also be significantly improved as it can be seen in Fig. 8(c), where AODV's end-to-end delay for clustered urban networks is 4 times larger than OLSR's, but ends up being identical for larger road lengths.

We further carry on the analysis of urban traffic distribution and its effects on AODV and OLSR. On the next set of figures, we increase the number of vehicles in the urban area, while reducing the transmission range in order keep the average network density constant (in terms of average number of neighbors per vehicles). We indeed want to spot out results solely dependent on the urban traffic distribution and not on effects on the MAC layer or on routing protocols from an increased number of neighbors. The average road length in this set of figures is set to 150m. By increasing the number of vehicles and keeping fixed average road length, we actually increase the interaction of each car with its environment, which in turn limits its ability to reach a desired speed.

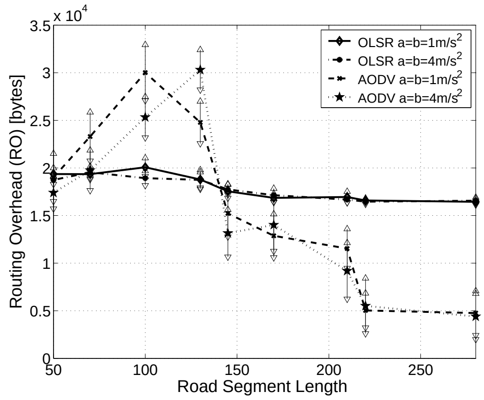
On Fig. 9(a), we see that neither AODV nor OLSR outperforms the other in term of PDR. Although both protocols are sensitive to urban traffic, OLSR is less dependent to this clustering effect as it accentuates its gap with AODV as the number of vehicles increases. In Fig. 9(b), we find a similar results as Fig 8(b) where AODV produces less control traffic than OLSR in a non-clustered urban environment, a situation that is reversed for clustered urban environments. Similarly, the AODV's end-to-end delay is significantly increased by an increased clustering effect at intersections.

In both sets of simulations, we however could not see a clear effect of the acceleration, resp. deceleration rate on AODV or OLSR's performance. This comes from the homogeneous distributions of vehicles. Indeed, VMM is not able to model heterogeneous vehicles with different accelerations (a), resp. deceleration (b) rates. And the advantage of an increase (a) or (b) is only beneficial if other vehicles have lower ones.

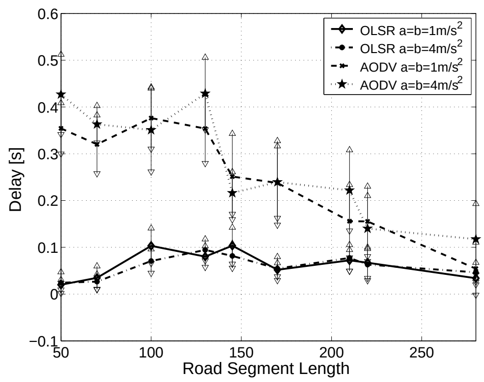
After having analyzed the effect of urban traffic distribution on the performance of routing protocols, we now illustrate the direct influence of data traffic rate and node density (in terms of average number of neighbors per vehicle) on AODV and OLSR performance. As we want to model urban environments, we fix the average road length to 50m and restore the transmission range to 100m. Fig. 10(a) shows the average PDR against the CBR throughput. The first observation we can make is that OLSR outperforms AODV on average by 200 %. This is a direct consequence from the previous analysis, which showed that AODV is clearly penalized by the non-uniform distribution of vehicles in the urban environment (see Fig. 8(a)). The second observation we can make is that, although both protocols experience a performance decay with the increase of the data traffic rate, the decay is less pronounced for AODV. When the rate of route discoveries is small, so is the probability for intermediate nodes to know an active route to a destination node. Consequently, a large number of AODV route requests (RREQ) must travel up to the destination node. However, as the data rate increases, so does the chance for intermediate nodes to have cached active routes, while OLSR must completely



(a) Packet Delivery Ratio (PDR)

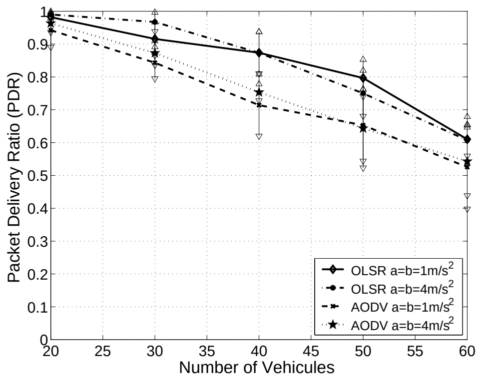


(b) Routing Overhead (RO)

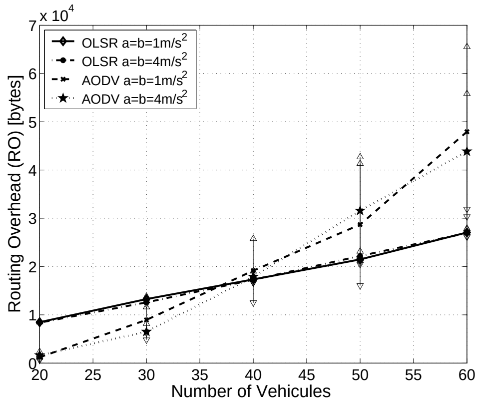


(c) End-to-end delay

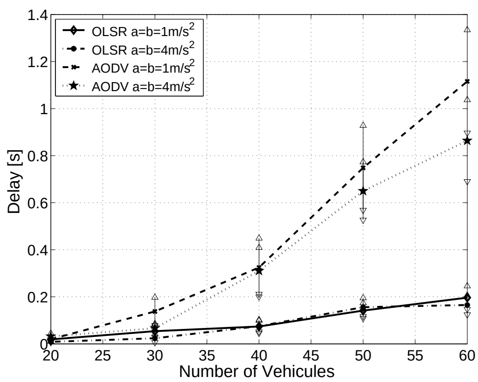
Figure 8: Performance evaluation of AODV and OLSR as a function of the average length of the roads segments



(a) Packet Delivery Ratio (PDR)



(b) Routing Overhead (RO)



(c) End-to-end delay

Figure 9: Performance evaluation of AODV and OLSR as a function of the average length of the number of vehicles at a fixed average density (Clustering Effect)

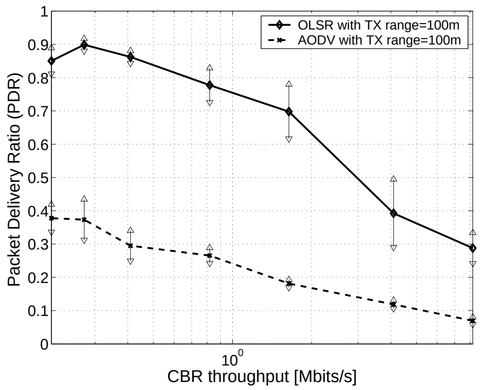
reconfigure its routing tables, a procedure that further restricts the channel access and reduces active routes for data traffic.

The Routing Overhead (RO) is depicted in Fig. 10(b). We actually see that the old cleavage between proactive and reactive routing protocols does not exist in VANETs. OLSR control traffic is always lower than AODV's, since the cost of repeated route discovery procedures in AODV introduces a large control traffic overhead. Note that this result is consistent with Fig. 11(b) as we used a network density of 12 for this scenario. We also observe that the control traffic of OLSR exhibits the expected characteristics of being independent of the data traffic rate. At very high data rates, the AODV's RO drops significantly, a feature that could be explained by the saturation of the MAC layer.

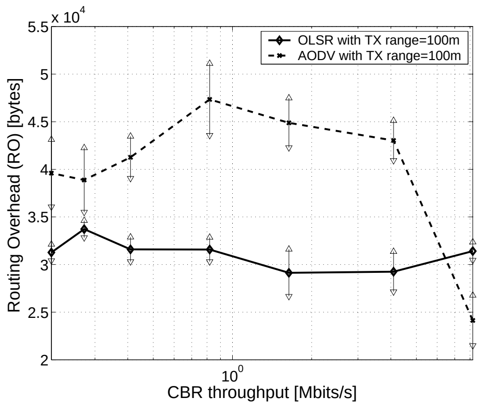
Finally, we show in Fig. 10(c) that OLSR consistently presents the lowest delay, regardless of data traffic. This may be explained by the fact that OLSR, as a proactive protocol, has a faster processing at intermediate nodes. When a packet arrives at a node, it can immediately be forwarded or dropped. In reactive protocols, if there is no route to a destination, packets to that destination will be stored in a buffer while a route discovery is conducted. Accordingly, the performance improvement in terms of delay raises up to 3 times between AODV and OLSR.

In the next set of figures, we display results obtained for the fourth scenario. Node density is defined as a node's average number of neighbors and is computed as mentioned in Table 1. Similarly to Fig. 10(a), Fig. 11(a) shows that OLSR outperforms AODV by up to almost 300% for highly dense networks. In order to analyze this graph, we divide the graph in three regions: locally *supra-critical, critical, and super-critical* [3] densities. We use the term *locally* because, due to the clustering effect, the network may not be connected even with a high density of nodes. However, within each cluster, *supra-critical, critical, and super-critical* densities appear, which create locally connected components of varying size. In the supra-critical density (8 nbrs/vhcl and below), OLSR is able to benefit from an increasing network density, whereas AODV has a stable PDR. When cars are aggregating in intersections, the MPR nodes become more stable, which increases the stability of OLSR and helps improving OLSR PDR. Then, above a critical density (8 - 10nbrs/vhcl), OLSR's shows initial signs of decrease. Indeed, in the super-critical category, as the density of car locally increases, the periodic maintenance of OLSR reduces its capability of accessing the channel for data traffic, while AODV's RREQ packets have a high chance to find a close intermediate node with an open route. An interesting remark may be made by comparing Fig. 9(a) and Fig. 11(a). We see on Fig. 9(a) that AODV's PDR is penalized by the clustering effect, at a constant network density. Accordingly, AODV is able to improve its PDR as we increase the network density, but the increased cluster effect reduces its performance. As the configurations used to obtain the results displayed in Fig. 11(a) include both the influence of the increased number of neighbor and

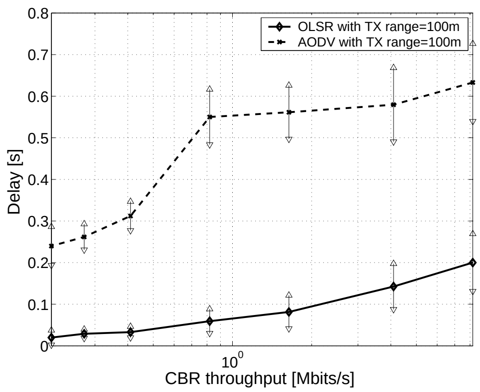
[3] Critical, supra-critical or super-critical are usual terms employed in percolation theory, referring to supra- or super- critical node densities for a network to percolate.



(a) Packet Delivery Ratio (PDR)



(b) Routing Overhead (RO)



(c) End-to-end delay

Figure 10: Performance evaluation of AODV and OLSR as a function of Data Traffic Rate

the non-uniform distribution of urban traffic, the effects are mutually exclusive and result to almost stable PDRs.

The next figure depicts the RO of OLSR and AODV as a function of the node density. We can see on Fig. 11(b) that, as we would expect, both ROs increase with the density. We clearly see a transition threshold for the control traffic generated by OLSR and AODV. For node densities below 8 nbrs/vhcl, the control traffic overhead of AODV is smaller than OLSR. However, as the density increases, the cost of repeated route discovery procedures in AODV introduces a large control traffic overhead, and OLSR ends up outperforming AODV up to 100%.

Finally, Fig. 11(c) depicts the end-to-end packet delay. As the access to the channel becomes harder, the delay can be lowered when a RREQ finds an intermediate node with an active route. However, the penalty for not finding any intermediate node becomes prohibitive as the network becomes locally saturated. On the other hand, routes that OLSR could maintain despite the congested channel are ready to use.

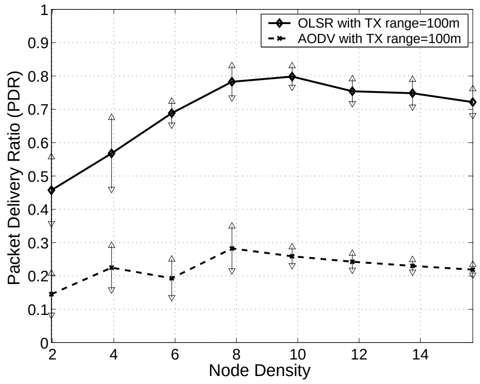
5 Conclusion

In this Chapter, we first illustrated how vehicular ad hoc networks in urban environment experience particular motion patterns which cannot be properly described by standard parameters. Indeed, the traffic regulations and the vehicles characteristics handled by the *VanetMobiSim Model (VMM)* create a clustering effect at intersection. This effect has remarkable properties on the spatial and temporal distribution of vehicles. The first one is that neither initial nor maximum velocity have a total influence on the real velocity in urban environments. Indeed, due to the interactions with the spatial environment and other neighboring cars, vehicles experience a non negligible speed decay. Then, a second property is the non-uniform distribution of urban traffic which locally increases the density of vehicles.

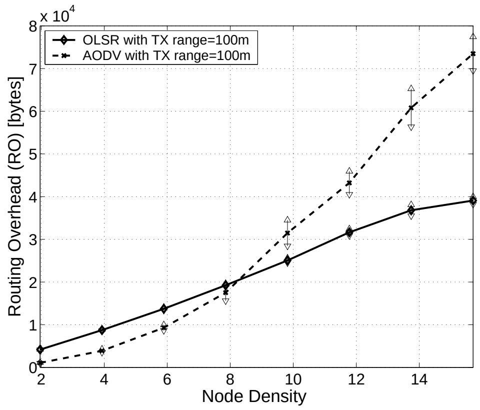
As neither the average velocity, nor the average density are able to control the spatial and temporal dependences generated by realistic urban vehicular motion patterns, we defined new meaningful parameters such as the *average length of road segments*, *the acceleration* or *the clustering effect*. By representing the true parameters of the topology or the mobility patterns, we illustrated how they have a significantly larger impact on the performance of AODV.

Another observation is that not only these new parameters are able to remarkably describe urban motions, but also these urban motions actually improve the performances of AODV, as they are significantly increased compared to those with Random Waypoint. These parameters become therefore an important key to more realistic performance evaluations of vehicular ad hoc networks in urban environments.

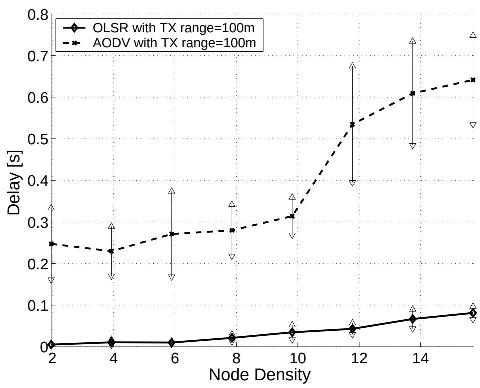
We then evaluated OLSR and AODV against urban-specific metrics such as road segment lengths or non-uniform urban traffic distribution, and against regular



(a) Packet Delivery Ratio (PDR)



(b) Routing Overhead (RO)



(c) End-to-end delay

Figure 11: Performance evaluation of AODV and OLSR as a function of Vehicular Density

metrics such as network density and data traffic rate. The obtained results we found showed that the performance of AODV is significantly influenced by the non-uniform distribution of urban traffic that is experienced in urban environments. We showed how OLSR outperforms AODV for almost all performance metrics we used. OLSR may be seen as a good candidate for VANETs routing protocols in urban environments.

This result is in complete contrast to previous studies, which have either concluded, at best, that reactive protocols were almost identically performing, or even outperforming proactive schemes. The main conclusion from this Chapter is that urban environments with realistic mobility patterns have a major impact on VANETs routing protocols, and accordingly make OLSR a better candidate for routing in urban environment than AODV.

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