Evaluating Vehicular Radio Connectivity with Environment-Based Metrics

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***Abstract* —Modeling radio wave propagation by a perfect circle around a transmitter is absolutely wrong. Obstacles effect must be considered especially in obstructed environments. In this paper we present a propagation model for vehicular network which takes into account the impact of physical obstacles present in the environment on electromagnetic wave propagation. Based on this model, we present a study of mobile connectivity for vehicular network in city environment. The considered area is a real map to which is added information on terrain type and zones attraction power. This information is used in both propagation and mobility models. We define several metrics characterizing radio connectivity and examine the effect of vehicles density and obstacles on this metrics. The study shows that when obstacles are ignored, the results are really optimistic in comparison with reality.**

I. Introduction

Vehicular networks are a particular class of wireless networks composed of vehicles equipped with wireless radio interfaces. They are mainly designed to improve drivers' conditions by allowing them to obtain information on road traffic conditions. Two communication types can be distinguished in such networks: Vehicle-to-Infrastructure communications in which vehicles are connected to fixed stations located on the roadsides for information exchange or Internet access; Vehicle-to-Vehicle communications, where vehicles exchange information without relying on any fixed entity. They collaborate to form at each time a dynamic distributed system called VANET (Vehicular Ad hoc Network).

In ad hoc networks, the possibility of establishing communications and the quality of exchanged messages depend on the radio connectivity between nodes. One factor that affects considerably this connectivity is nodes motion, particularly when nodes move at high speeds as it is the case for vehicular networks. Several models have been proposed to simulate nodes mobility in MANET [1]. These models ignore the key characteristics of vehicular traffic, mainly the constraints on nodes movement and the interactions between neighboring nodes; they are thus not suitable for VANET. Aiming to reflect as closely as possible the real behavior of vehicular traffic, new models have been proposed [2]. Depending on the level of detail considered, these models may be classified into two categories: *macroscopic models* that take into account parameters such as road topology, roads attributes, traffic signs and traffic characteristics (density, flow etc.) and *microscopic models* that focus on the individual behavior of each vehicle and try to model features such as speed, acceleration, braking and interactions between vehicles.

The second factor which plays an important role on network connectivity is the environment in which radio signals propagate. Indeed, signal deteriorations depend on the type and the density of physical obstacles present in the environment. The effect of these obstacles must be taken into account in one radio wave propagation model. However the majority of studies done on ad hoc networks neglects this parameter and assumes a flat surface where transmission range is modeled by an ideal circle around each node, then radio propagation is constant which is absolutely wrong.

The evaluation of the impact of parameters such as nodes density, nodes velocity and obstacles on network connectivity is a good starting point for analysis, improvement or development of routing strategies. However, there are few studies in the literature on radio connectivity in VANET. The authors of [3] considered an unobstructed highway and studied the impact of transmission range on routes lifetime. In [4], vehicles are assumed to travel at their maximum velocities in an unobstructed highway. The authors examined the effect of density, velocity and distance between communicating vehicles on connections lifetime. The considered environment in [5] is an urban environment where vehicles move in a road topology extracted from a real city map. The authors analyzed the average nodes degree for various traffic flow condition, transmission range and time interval. They also presented an algorithm for computing the transitive connectivity. To demonstrate the impact of employed mobility model on vehicular network topology, Fiore and Härri [6] studied the network connectivity under various mobility models based on different approaches and simulated vehicular motion with different levels of realism. The authors considered a simple grid road topology and examined link duration, nodal degree and network clustering.

In this paper, we present a study of vehicular network connectivity in a real urban environment. Unlike the above mentioned works that assume an unobstructed environment and model the communication range by a simple circle around the transmitter, we define and use a propagation model to capture obstacles effect on radio signals. The considered city map is divided into cells of equal size each characterized by information representing its ability to attract vehicles, its altitude and type of structure located in the cell. This information is taken into account in both mobility and propagation models. We conducted two series of tests. In the first one, we consider different traffic densities and examine nodes degree, connections lifetime, dominated nodes rate and cluster formation. In the second series of tests, we evaluated the performance of two routing protocols. The topology-based routing protocol AODV (Ad-hoc On-Demand Distance Vector) [7] and the geographical routing protocol GPSR (Greedy Perimeter Stateless Routing) [8]. The evaluated metrics are packets delivery ratio and average hops number. To show the importance of taking into account the impact of obstacles on radio signal propagation, we also evaluate all metrics assuming an unobstructed flat environment.

The remainder of this paper is organized as follows: Section 2 presents the propagation model and its adaptation to our case study. Section 3 briefly describes the mobility model we used. Simulation environment and results are presented in Section 4. Finally, Section 5 concludes the paper.

II. Propagation model

The propagation model employed in our simulations is based on the statistical path loss model defined in [9] for suburban environments. This model uses empirically measured data collected across the United States in a large number of existing macrocells that cover a wide range of terrain types. It contains three terrain categories: category A that corresponds to a hilly terrain with moderate-to-heavy trees densities, this category has the maximum path loss values; the middle category, B, characterized as either mostly flat terrain with moderate-to-heavy trees densities or hilly terrain with light tree densities; the last category, C, is mostly flat terrain with light tree densities, lowest path loss values are obtained with this category. The path loss formula is:

$$PL = A + 10\gamma \log_{10}(d/d_0) + s \qquad d \geq d_0 \qquad (1)$$

where

$$A = 20 \log_{10}(4\pi d_0/\lambda) \qquad (2)$$

$$\gamma = (a - bh_b + c/h_b) + x\sigma_\gamma \qquad (3)$$

$$s = y(\mu_\sigma + z\sigma_\sigma) \qquad (4)$$

d is the distance between the base antenna and the mobile antenna, A is a fixed quantity corresponding to the free-space path loss where d_0 = 100m and λ is the wavelength in meters. The path loss exponent γ is a Gaussian random variable over the population of macrocells within each terrain category. In (3) h_b is base station antenna height in meters, x is a zero-mean Gaussian variable of unit standard deviation, N[0, 1] and a, b, c and σ_γ are data-derived constants for each terrain category. s is the shadow fading component, it varies randomly from one location to another within any given macrocell; y and z are both zero-mean Gaussian variables of unit standard deviation, N[0, 1] and μ_σ and σ_σ are data-derived constants for each terrain category.

We did improvement to this model to adapt it to our environment and to our numerical data. The environment considered in our study is a real city map (urban environment). The area is divided into equally sized cells each characterized by its altitude and the percentage of each type of structure presents in the cell (e.g. 20% of building with height <10, 10% forest...). Each cell is at first classified as *building* or *forest* by comparing the percentage of forest to the sum of percentages of building located in the cell. Categorization according to the path loss model is determined as follows: all cells with a percentage of building less than 33% belong to category C, those with a percentage between 33% and 66% belong to category B and the rest of cells fall into category A. The path loss is computed at the center of each cell, the obtained value is assumed the same throughout the cell. Only cells located at a distance less than d_{max} from the transmitter are considered. Beyond this distance the received signal strength is assumed null. To compute the path loss between two cells G_t (transmitting antenna location) and G_r (receiving antenna location) the total distance d_t crossed by a signal over each terrain category situated between G_t and G_r is determined. The new path loss formulas are:

$$PL = \begin{cases} A + 10\gamma \log_{10}(d/d_0) + s & d \geq d_0 \\ 20 \log_{10}(4\pi d/\lambda) + s & d < d_0 \end{cases} \qquad (5)$$

$$\gamma = \frac{1}{d} \sum_{t=1}^{T} \gamma_t d_t \qquad (6)$$

$$\mu_\sigma = \frac{1}{d} \sum_{t=1}^{T} \mu_{\sigma t} d_t \qquad (7)$$

$$\sigma_\sigma = \frac{1}{d} \sum_{t=1}^{T} \sigma_{\sigma t} d_t \qquad (8)$$

γ, μ_σ and σ_σ are the averages computed over all terrain categories located between G_t and G_r and $T \in [1,3]$ is the number of these categories. The height difference h_b between transmitting and receiving antenna is calculated taking into account cells altitude (altitude of G_t and G_r).

III. Mobility model

The mobility model we used is V-MBMM (Vehicular-Mask Based Mobility Model) [10] which is an adaptation of the individual mobility model MBMM [11][12] to VANET. The road topology is extracted from a real map. All roads are modeled as bidirectional roads with single lane in each direction. Roads are weighted with dynamics values representing their attraction power to drivers. These attractions are determined based on survey data and information on terrain characteristics and urban infrastructures; their values vary every fifteen minutes. Traffic at intersections is regulated by means of traffic lights. At microscopic level, V-MBMM employs the *Intelligent Driver Model* (IDM) [13]. This model falls into the car following models category and thus characterizes the behavior of each driver according to its preceding vehicles. Whenever a vehicle reaches an intersection, it chooses the next direction to take according to a Markov chain which takes into account roads attraction powers. Two coefficients based on traffic density on roads and previous movements taken by a vehicle are applied to each Markov chain in order to inhibit unrealistic displacements. A full description of the model is in [10].

IV. Simulation and results

We used the application "*Territoire Mobile*" (TM) for simulation. This application represents the city of Belfort in the north-eastern of France. Several data have been used to reproduce the real environment including GIS shapefiles representing the city map, survey data and socio-economical information collected by professionals for regional planning needs. The area is divided into square cells, each characterized by the types of structure located in the cell (roads, buildings, forest...), cell altitude and cell attraction power for vehicles. The mobility and the propagation models have been integrated to the application by considering only those cells that are roads. In other words, the mobility is restricted to road cells and the path loss is only computed for those cells but it takes into account all obstacles between transmitters and receivers even outside the roads.

An undirected graph *G* (*V*, *E*, *t*) is generated every *T* seconds. The set *V* of vertices represents vehicles and an edge e_{ij} connects two vertices v_i and v_j belonging to *E* if vehicle *i* is in the transmission range of vehicle *j* and vice versa. Figure 1 shows an example of a graph obtained with 100 vehicles.

A. Metrics

In all simulations we vary the nodes density. From the generated graphs we estimate four metrics that are:

Figure 1. Initial connection graph for 100 vehicles distributed in an area of 2500m*2500m.

- *Nodes degree*. It is an important indicator of the possibility or not to establish communication sessions between nodes in one ad hoc network. The average degree of node n_i over all graphs is:

$$d(n_i)=\frac{1}{N}\sum_{k=1}^{N}|Ngb_{ik}| \qquad (9)$$

where *N* is the total number of graphs generated during simulation and Ngb_{ik} is the set of all nodes connected to a node n_i in a graph *k*.

- *Connections lifetime*. This metric provides information on network stability. Low values indicate that network topology is frequently changing. For more precision, instead of computing only a single value that represents the average connection duration, we define intervals of increasing duration and compute for each one the rate of connections whose duration value belongs to the interval. An *age* value is maintained for each connection. The *age* is initialized to the value *T* when the connection appears. For each new generated graph, we check if the connection still exists. If so the value *T* is added to *age*, otherwise the number of connections of the interval that contains *age* value is incremented by 1.

- *Dominated nodes rate*. This metric gives a general idea on the rate of redundancy and thus the probability of collisions that may occur in the network mainly because of broadcast transmissions of data or control packets. This can be very common in VANET with high nodes density and vehicles queuing at road intersections. We consider that a node n_i is dominated by its neighbor n_j if all the neighbors of node n_i are also neighbors of node n_j. Therefore, messages dissemination by node n_i may be unnecessary.

- *Clustering*. In vehicular networks, entities tend to move in groups formed mainly because of vehicles stop at intersections and traffic congestion on roads. This phenomenon favors the use of hierarchical routing strategies instead of a flat routing in order to limit messages dissemination in the network. Thus, the latter factor we analyze is the formation of clusters in the network. We define a cluster as a set of nodes connected to a master node (cluster head) and whose the number of hops from that master is less than a predefined value *Hpmax*. To determine a cluster, we consider at each step all the nodes that are not part of any cluster and select as a cluster head the node with the maximum number of neighbors. This is achieved by the following algorithm:

Clustering Algorithm

Variables:
V: set of simulated nodes.
CS: set of identified clusters.
c: current cluster.
ch: node selected as a cluster head.
AS: the set in which the algorithm selects the members of *c*.
$N_S(n_i)$: the set of neighbors of node n_i in the set *S*.
Hpmax: maximum number of hops from the cluster head to any other member of the cluster.
$NbHp(n_i, n_j)$: number of hops from node n_i to node n_j.

Algorithm:
$CS := \Phi$, $AS := V$;
while $\exists\, n_i \in AS / |N_{AS}(n_i)|>0$
begin
    $c := \Phi$;
    $ch := n_i \in AS / |N_{AS}(n_i)| = \max \{|N_{AS}(n_j)| / n_j \in AS, j = 1 .. |AS|\}$
    $c := c \cup N_{AS}(ch) \cup \{ch\}$;
    $AS := AS/c$;
    while $\exists\, n_k \in c / (|N_{AS}(n_k)|>0$ and $NbHp(ch, n_k)<Hpmax)$
    begin
        $c := c \cup N_{AS}(n_k)$;
        $AS := AS / N_{AS}(n_k)$;
    end
    $CS := CS \cup c$;
end

When the value of *Hpmax* is set to infinity this algorithm returns the isolated groups of nodes in the network that we denote by *fragment* in the remainder of this paper.

The last two metrics relate to routing protocols:

- *Packets delivery ratio*. It represents the ratio between the number of data packets sent by the source and the number of data packets received by the destination. A routing protocol that does not take into account the main characteristics of a network such as the problem of network fragmentation and short connections lifetime, leads to a higher data loss rate.

- *Average hops number.* This metric corresponds to paths length. It represents the number of times that a data packet has been forwarded before reaching the final destination. The small average values indicate that only communications with a small number of hops succeed. The main causes are frequent route breakages and network fragmentation.

B. Results

Simulations were performed on an area of 2500m*2500m divided into cells of 25m*25m. We vary the number of vehicles from 50 to 400 and set the maximum speed to 15m/s. The numerical values of all constants related to the terrain categories contained in the path loss model are the same as in [9]. To show the impact of obstacles on network connectivity, we also estimate the four metrics by considering circular transmission ranges of 200m radius. All simulations run for 3,600 seconds, the measurements are recorded after the first 900 seconds to exclude initiation phase. Connection graphs are updated every one second. In the remainder of this paper we use the notation *TC* (*Terrain Characteristics*) to refer to the propagation model that takes into account terrain characteristics and the notation *TR* (*Transmission Range*) in reference to the propagation model that uses simple circles as transmission ranges.

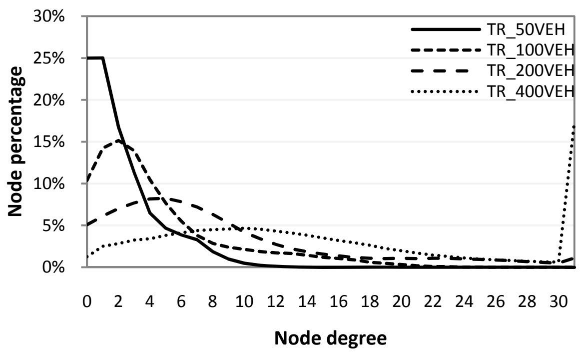

Figure 2. Nodes average degrees distribution obtained with TR.

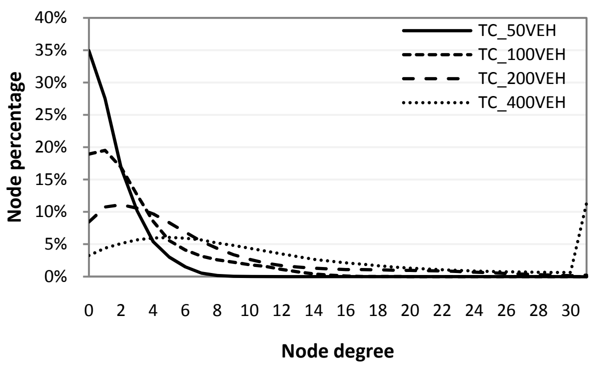

Figure 3. Nodes average degrees distribution obtained with TC.

Figures 2 and 3 depict vehicles percentage versus average degree values obtained respectively with TR and TC. As expected, the results show that the average degree increases when vehicular density grows. By comparing the curves obtained with TC to those of TR we can notice that ignorance of obstacles impact leads to optimistic results on nodes connections. With TC, the percentage of isolated nodes is 3% when the number of simulated vehicles is 400, this value increases with decreasing node density to reach 35% when the density is 50 vehicles. With TR, the percentages are respectively 1% and 25%. From the figures, it can also be observed that for small average degree values TC presents higher percentages. However, for high values (above 2, 3, 6 and 10 respectively for a density of 50, 100, 200 and 400 vehicles) results obtained with TR are higher. Generally, and as it can also be seen in Figure 4 that shows the average degree value for all simulated nodes, the results obtained with TR are optimistic that is the connections between nodes are less important so communications are more difficult than estimated.

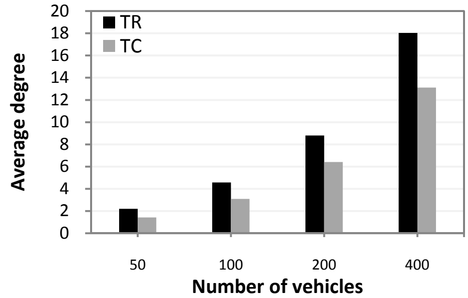

Figure 4. Average nodes degree vs. Nodes density.

Measurements on connections lifetime are depicted in Figures 5 and 6. The duration intervals, in seconds, considered in simulations are [0, 4[, [4, 10[, [10, 20[... Each interval is represented on the graph by its upper bound. Both figures show that the density has almost no effect on connections lifetime. The reason is that no congestion situation occurs for all considered densities and thus the average velocity is almost the same. Therefore we discuss two factors that are the effect of obstacles on connections lifetime and connections lifetime distribution regardless of nodes density.

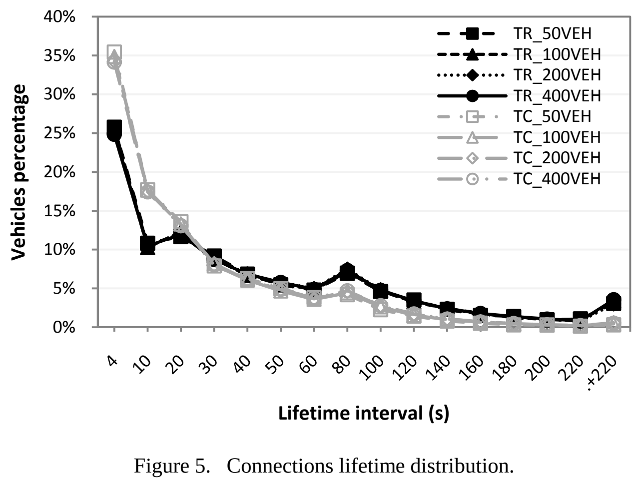

Figure 5. Connections lifetime distribution.

As for the average degree, it can be observed that the results obtained with TR are higher, too optimistic, compared to those with TC. Figure 6 shows that the average connections lifetime value obtained with TR (48 seconds) is the double of that obtained with TC (24 seconds). With TR, the connectivity is only affected by vehicle displacements, however, with TC the effect of real obstacles is also taken into account. The results on average connections lifetime indicate that the impact of obstacles is as important as that of mobility (lifetime halved). When focusing on the connections lifetime distribution, it can be seen from Figure 5 that more than 63% of connections with TR and 65% with TC have the duration less than the average value. The curves show that about 25% of connections with TR and 35% with TC have a lifetime value not exceeding 4 seconds. This indicates that network topology is continuously changing but much more than expected with circle range.

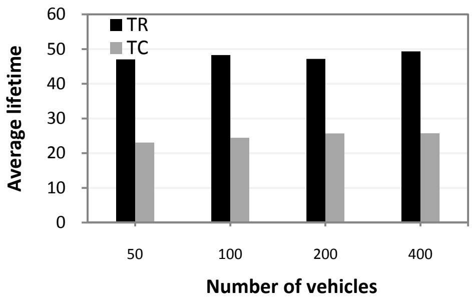

Figure 6. Average connections lifetime vs. Nodes density.

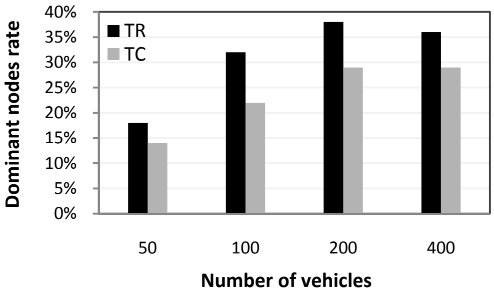

Figure 7. Dominated nodes rate vs. Nodes density.

The dominated nodes rate obtained for all densities values, from 50 up to 400, is given in Figure 7. It can be observed that the values are quite high. With TR, at a density of 50 vehicles the number of dominated nodes is 9; this value increases when vehicular density grows to reach 144 for a density of 400 vehicles. With TC, the number of dominated nodes, for each density, is smaller compared to that obtained with TR; it is 7 and 116 for the densities of 50 and 400 vehicles respectively.

We did another series of tests to study the clustering formation in the network. We considered two values of *Hpmax*. In order to analyze network fragmentation, we first set *Hpmax* value to infinity. In the second series of tests we limited the number of hops from the cluster head to 4. The results are shown in Figures 8 and 9. The notation FRG refers to the fragmentation and CLS to clusters with *Hpmax* set to 4. We can observe that at low density of vehicles, the results obtained with TR are almost equal to those obtained with TC; the difference becomes significant when vehicular density grows. Figure 8 shows that at low density, that is 50 vehicles, the number of fragment is almost equal to the number of clusters. The reason is that given the low nodes density, the maximum number of hops from the cluster head in each fragment does not exceed 4 and therefore the clusters formed with *Hpmax* set to 4 are all isolated groups of nodes. Obviously, the average number of nodes per cluster is in this case equal to the average number of nodes per fragment. Increasing vehicle density magnifies the difference between clusters and fragments. At high densities the network becomes more connected leading to larger fragments in terms of number of hops from the cluster head and average number of nodes per fragment. With TR, for a density of 400 vehicles, the number of fragments is 6.27 and the average number of nodes per fragment is 62.88. The number of clusters is much higher; it is 14.53 with an average number of nodes per cluster equal to 27.38. With TC the number of fragments (clusters) is 16.48 (24.13) and the number of nodes per fragment (cluster) is 23.49 (16.16). Everything concludes that VANET cannot be simulated with confidence without a right modeling of connection. Most of time, the error ratio on connection features is equal to 2.

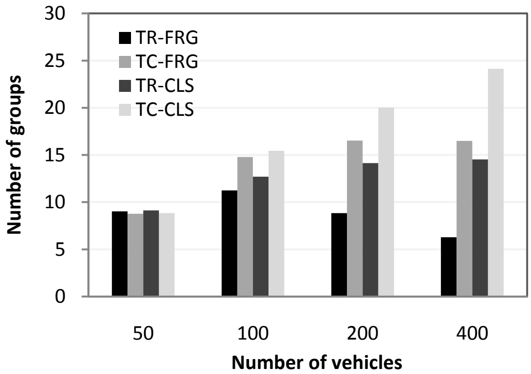

Figure 8. Number of groups vs. Vehicles density.

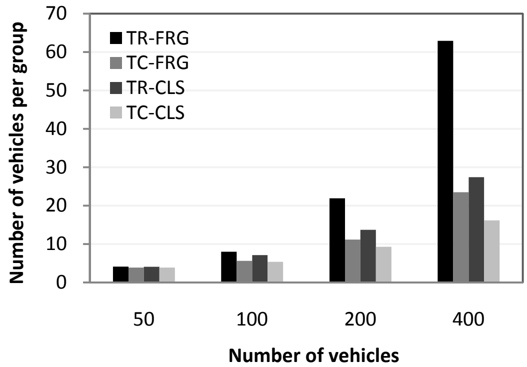

Figure 9. Average number of vehicles per group.

In order to evaluate routing performance, we used the application *Territoire Mobile* (TM) for mobility and signal propagation modeling and the simulator NS2 [14], version 33, for network modeling. Traces describing vehicles displacements in the territory are generated in TM and used as movement scenario files in NS2. For signal propagation aspect, for each road cell we calculated the received signal power from all road cells located at distance less than d_{max} using TM. The generated file is used as input of NS2; it allows determining the coverage area of each vehicle as a function of its position.

The simulations were performed considering an area of 1500mx1500m from Belfort downtown. We varied the number of vehicles from 60 up to 120 and set the duration of each scenario to 200s.

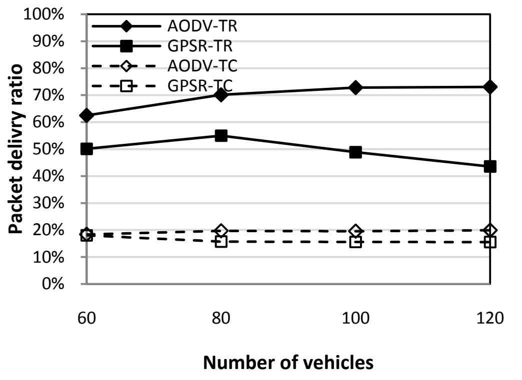

Figure 10. Packets delivery ratio vs. Number of vehicles.

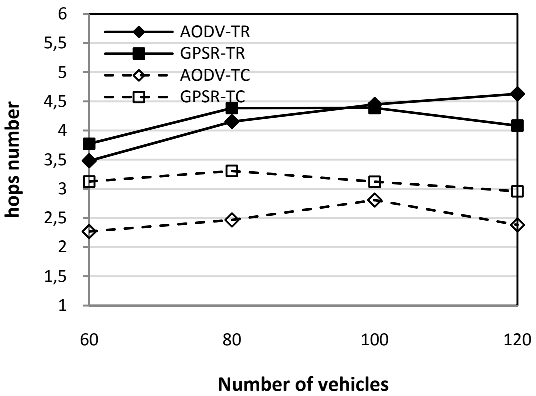

Figure 11. Average hop counts vs. Number of vehicles.

As expected, Figure 10 shows the degradation of the reception rate in TC (*Terrain Characteristics*) compared to TR (*Transmission Range*) in both protocols. In AODV the packets delivery ratio varies between 60% and 70% with TR. It is less than 20% with TC. GPSR shows a similar behavior with a delivery ratio between 42% and 52% with TR and 15% and 19% with TC. The low reception rate in TC is caused by network instability. Since obstacles impact on radio signals is considered, the connections appear and disappear more frequently. Moreover, nodes coverage areas are smaller thus exacerbating the problem of network fragmentation and leads to multi-hop communications failures. Indeed, Figure 11 shows that with TR, the average hops number is greater compared to that with TC for all vehicular densities. The average with TR is 4.17 in AODV and 4.15 in GPSR. With TC the values are respectively 2.48 and 3.12. All these results show the importance of taking into account the characteristics of the environment in the evaluation of solutions proposed for vehicular networks.

V. CONCLUSION

In this paper we presented a radio signals propagation model for vehicular network. The contribution of this model is that it reflects environment characteristics by defining three terrain categories according to obstacles density; radio signals are more attenuated in the presence of obstacles. In order to show the impact of radio propagation modeling on vehicular networks connectivity, we defined several metrics which we evaluated using two models. The first one assumes an unobstructed flat space and represents node transmission range by a simple circle. The second is the model we have defined that considers obstacles effect on radio signals. The first metrics we evaluated are nodes degree, connections lifetime, dominated nodes rate and cluster formation. The results have shown that when obstacles are ignored, the values obtained with all metrics are optimistic with an error rate equal to 2 most of the time. The last two metrics we defined, packet delivery ratio and hop count, relate to routing protocols. The evaluation results obtained with the two routing protocols AODV and GPSR showed that when terrain characteristics are considered, the delivery rate decreases by one third while only communications over a small number of hops succeed.

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