Proceedings of the IEEE ITSC 2006
2006 IEEE Intelligent Transportation Systems Conference
Toronto, Canada, September 17-20, 2006

Minimum Transmission Range in Vehicular Ad Hoc Networks over Uninterrupted Highways

Maen M. Artimy, William Robertson, William J. Phillips

Abstract— **This paper discusses the impact of the non-homogeneous distribution of vehicles on the connectivity of Vehicular Ad Hoc Networks (VANETs). The non-homogeneous distribution of vehicles results from traffic jams caused by bottlenecks in the transportation networks and by fluctuations in vehicles' speeds. The discussion in this paper is applicable to a VANET in a long stretch of a highway with few lanes and without interruptions caused by intersections or entry and exit ramps.**

Our main contribution is the formulation of new relationship that provides a tighter estimate for the lower bound of the Minimum Transmission Range (MTR) in VANETs by considering the phase separation in vehicle traffic. This relationship is an improvement to the estimate of the MTR given previously in the literature for one-dimensional networks of homogeneous node distribution.

I. INTRODUCTION

The most fundamental property in any communication network is the connectivity among its nodes. Mobile Ad Hoc Networks (MANETs) face the difficult challenge of maintaining connectivity so that a node may establish a communication link to any other node in the network. The connectivity of the network is affected by several factors including transmitter power, environmental conditions, obstacles, and mobility.

Extensive research is dedicated to determine the Minimum Transmission Range (MTR) in MANETs. The MTR corresponds to the minimum common value of the nodes' transmitting range that produces a connected communication graph. The motivation behind this research is the difficulty, in many situations, to adjust the nodes' transmitting range dynamically, making the design of a network with a static transmitting range a feasible option. It is also known that setting the nodes' transmitting range to the minimum value minimizes energy consumption while maximizing network capacity [1].

A Vehicular Ad Hoc Network (VANET) constructed among vehicles in a highway can be viewed as an example of one-dimensional MANETs. It is shown in [2] that connectivity in one-dimensional networks can be maintained only over short distances. Previous analytical approaches to determine the MTR in such networks are based on the assumption that the network nodes are distributed in a homogeneous manner along a line. In other words, the distribution of the nodes in any segment of the line is representative of the distribution in the other segments.

Authors are with the Faculty of Engineering, Dalhousie University, artimym@dal.ca, bill.robertson@dal.ca, william.phillips@dal.ca

This paper discusses the impact of the non-homogeneous distribution of vehicles on the connectivity of VANETs and the value of MTR in finite-length highways. The non-homogeneous distribution of vehicles is caused by traffic jams, which are a common phenomenon in the modern networks of streets and highways. Traffic jams are not only caused by constraints in the transportation network, but also by fluctuations in vehicles' speeds whose effect intensifies as the vehicle density increases [3]. We find that previous analytical approaches that assume a homogeneous node distribution underestimate the MTR value in VANETs under congested traffic conditions.

We used the Nagel and Schreckenberg (NaSch) vehicle traffic model [4] as the main analytical tool to derive the relationship for the lower bound MTR. Simulations of vehicle traffic using *RoadSim* [5] are employed to verify the analytical estimates for the lower bound MTR and provide an empirical estimate for the upper bound of the MTR. All simulations are carried out in 1- and 3-lane highway configurations.

The paper is organized as follows. A summary of the related literature is provided in Section II. The NaSch model and the separation of traffic phases are introduced in Section III. The lower-bound MTR is derived in Section IV. Simulation experiments and their results are described in Section V. The conclusion to this paper is given in Section VI.

II. RELATED WORK

If all node positions in a network are known, the MTR is determined by the length of the longest edge of the Euclidean Minimum Spanning Tree (MST) in a geometric graph composed of all nodes [6]. In the most realistic scenarios, node positions are unknown but it can be assumed that the nodes are distributed according to some probability distribution in the network. In the latter case, it is necessary to estimate the MTR that provides connectivity with a probability that converges to 1 as the number of nodes or the network size increases.

In the probabilistic approaches to determine the MTR, authors have relied on the theory of geometric random graphs (GRG) to represent wireless ad hoc networks [7]. A network can be modelled by a graph $G(V, r_c)$ in which two nodes are connected if the Euclidean distance between them is no more than r_c. Most studies consider how the transmission range is related to the number of nodes n, dispersed according to a uniform or Poisson distribution in a fixed area (or line). The continuum percolation theory and the occupancy theory have also been used in the probabilistic analysis of ad hoc networks.

In the case of one-dimensional models, Piret [8] discussed the coverage problem to find that the lower bound of the transmission range, r_{cover}, for nodes located according to the Poisson distribution in a line of length L, with density k, is $r_{\text{cover}} = \ln(Lk)/(2k)$. The author shows that, if $r_c = m\, r_{\text{cover}}$, then the connectivity, $Q(\cdot)$ among nodes approaches 1 (i.e. $\lim_{L\to\infty} Q(r_c, L) = 1$) when $m > 2$, where m is a constant.

Santi and Blough [9] provide tighter bounds on MTR using occupancy theory. Their primary result shows that when nodes are distributed uniformly over a line of length L, the network is connected if

$$r_c n \in \Theta(L \ln(L)) \qquad r_c \gg 1\ . \tag{1}$$

Dousse et al. [2] approach the connectivity problem in both pure ad-hoc and hybrid networks. They conclude that connectivity is limited to short range communications in one-dimensional and strip networks (two-dimensional networks of finite width and infinite length), because the network remains divided (with high probability) into an infinite number of bounded clusters. Since VANETs in highway environment can be represented as a one-dimensional or strip network, it can be concluded that it is not practical to maintain connectivity in the entire network that may stretch for tens of kilometres. Instead a VANET should tolerate a certain level of partitioning.

A relationship derived by Cheng and Robertazzi [10] predicts that the expected number of broadcasts needed to disseminate a message before a gap is encountered in a one-dimensional network increases exponentially relative to the product of transmission range and the node density. Desai and Manjunath [11] study connectivity in finite one- and two-dimensional networks and provide a probability for the existence of gaps.

The paper by Füßler et al. [12] focuses on free-flow VANETS. In the context of comparing various routing strategies, simulations are used to find the effect of the transmission range on the number of network partitions and provide an estimate of the transmission range that minimizes the partitions.

The analytical work presented above assumes that nodes are distributed homogeneously according to uniform or Poisson distributions in the network. In this paper, we discuss the effect of non-homogeneous distribution of vehicles.

III. Traffic jams and critical density

We used the Nagel and Schreckenberg (NaSch) vehicle traffic model as the main analytical and simulation tool for this work. The basic NaSch model [4] consists of a one-dimensional Cellular Automata (CA) grid of L cells and defines a set of rules for vehicle's movement through the grid. Each cell represents a small section of the road, which can be either empty or occupied by one vehicle. The vehicle may travel in one direction from one cell to another at integer speed of $[0, U_{\max}]$, which correspond to the number of cells a vehicle can advance in one time-step, provided that there are no obstacles ahead. The cell size is chosen to correspond to the reciprocal of maximum vehicle density, k_{jam} in traffic jams.

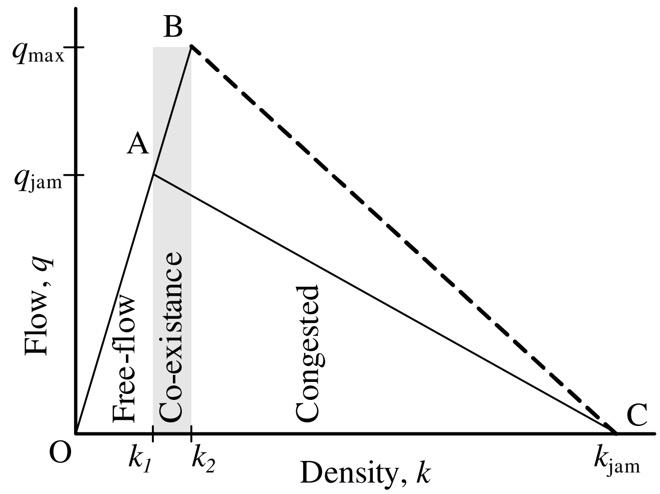


Fig. 1. The flow-density relationship.

A vehicle's speed is updated in each time step by calculating the gap to the lead vehicle. The gap size determines whether a vehicle can accelerate or slow down. Then, the vehicle may be moved to another cell according to its new speed. To add a stochastic behaviour to the system, the vehicle may not accelerate with a probability of p_{noise}. A sightly modified model, called the NaSch model with a slow-to-start rule (NaSch-S2S) assigns a higher value to the probability of not accelerating from the zero speed. The latter probability is denoted p_{s2s} [13].

We developed a traffic simulator, *RoadSim*, to generate vehicle traffic movement based on the NaSch-S2S model [5]. *RoadSim* adds several extensions to the original model to enable simulation of multi-lane traffic and traffic across intersections. *RoadSim* also generates network graphs, which will be used to determine the MTR values in the VANET simulations described in Section V.

RoadSim generates vehicle traffic whose flow, q (veh/hr) is related to the density, k (veh/km) by the fundamental diagram of road traffic shown in Figure 1. The figure shows that the flow-density relationship has two distinct modes of traffic flow, the free-flow traffic and the congested traffic. Traffic flow is also related to the average speed, u (km/hr) and the density of vehicles by [14],

$$q = u \times k\ . \tag{2}$$

In the deterministic case of the NaSch-S2S model (which is created when the randomization rule is dropped or, equivalently, when $p_{\text{noise}} = p_{\text{s2s}} = 0$), the traffic exhibits free-flow characteristics when all gaps between vehicles are equal to or greater than $U_{\max}$ so that vehicles are never forced to slow down. This situation arises when the system-wide density, k_L, of a closed system of size L, is smaller than the critical density, k_{det}. In the deterministic NaSch-S2S model, the critical density is [15],

$$k_{\text{det}} = \frac{1}{U_{\max}+1} \ . \tag{3}$$

Substituting (3) in the fundamental relationship (2) provides the maximum flow, which occurs at the density k_2 (point B in Figure 1),

$$q_{\text{det,max}} = \frac{U_{\max}}{U_{\max}+1} \ . \tag{4}$$

When stochastic behaviour is included in the NaSch-S2S model, gaps of size $U_{\max}$ are not enough to guarantee free-flow since fluctuations of the lead vehicle's speed may force the following vehicles to slow down and create traffic waves. Figure 1 shows three regions in the q–k relationship; only large disturbances create traffic jams; thus, forcing the free-flow traffic in the co-existence region to enter the congested region. Small disturbances force the traffic in the congested region to break into traffic jams [3].

In the NaSch-S2S model, small speed fluctuations are represented by the parameter p_{noise}. The slow-to-start probability, p_{s2s}, is the source for the large disturbances. In such a system, the flow in the free-flow and congested regions are given by [15], [16],

$$\begin{aligned} q &= u_f \times k \\ &= (1-p_{\text{s2s}})\,(1-k/k_{\text{jam}}) \ , \end{aligned} \tag{5}$$

where the average free-flow speed, $u_f = U_{\max} - p_{\text{noise}}$, and k is the vehicles' density. The lines representing the two modes of traffic meet at,

$$k_1 = \left(\frac{u_f}{1-p_{\text{s2s}}} + \frac{1}{k_{\text{jam}}}\right)^{-1} \ . \tag{6}$$

In equation (6) the density k_1 (of Figure 1) is the density value that separates the free-flow traffic from the co-existing traffic. Beyond this density value, the traffic is characterized by start-stop waves. When compared to the deterministic model, the critical density of the NaSch-S2S model is generally lower, $k_c < k_{\text{det}}$. However, our choice of randomization parameters ($p_{\text{noise}} = 0.01$) results in $u_f \approx U_{\max}$, and $k_c \approx k_{\text{det}}$.

IV. Estimation of lower-bound MTR in vehicular ad hoc networks

Jost and Nagel's analysis and simulations in [13] show that vehicles in free-flow conditions are distributed along the road according to a uniform distribution. It is concluded from the summary of the related work in Section II, that the work of Santi and Blough in [9] applies to an environment similar to free-flow vehicle traffic in a single-lane road.

In this section, an estimate for the lower-bound of the MTR is derived for VANETs in highways by considering the non-homogeneous distribution of vehicles along the highway in congested traffic. The derived lower-bound is based on the assumption that all vehicles are equipped with wireless transceivers so that they can be active nodes in the communication network. It is also assumed that vehicle mobility is described by the NaSch-S2S model.

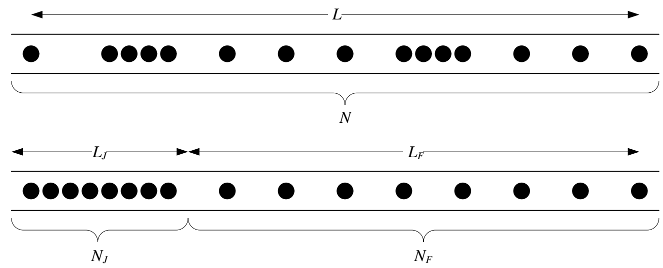


Fig. 2. Congested traffic in a highway section: a) Original distribution of vehicles; b) Consolidation of the free-flow and congested sections of the road.

The lower-bound proposed in [9] defines the minimum (critical) range, r_c in (1). For convenience, (1) is rewritten as an inequality,

$$r_c(k) \geq \frac{\ln(L)}{k} \ , \tag{7}$$

where k is the density of vehicles.

A congested traffic system can be characterized as patches of traffic jams separated by jam-free regions [15], as shown in Figure 2(a). In the vehicular network of Figure 2(a), the worst case MTR value depends only on the traffic of the free-flow region since the MTR in the jam region is easily estimated as $1/k_{\text{jam}}$. To continue the derivation of the lower-bound, suppose that all free-flow regions can be consolidated in one side of the road and all congested regions are consolidated in the other side, as illustrated in Figure 2(b). Since equation (7) can apply only to the free-flow section, the critical range within the section, r_{c,L_F}, is given as,

$$r_{c,L_F} \geq \frac{\ln(L_F)}{k_F} \ , \tag{8}$$

where L_F is the length of the free-flow section of the road and k_F, is the density of the traffic in the same section.

In a road such as the one shown in Figure 2, the flow of vehicles escaping the traffic jam, q_F, is a free-flow traffic that is virtually independent of the vehicle density. The value of q_F is determined by the average waiting time for the first vehicle in the traffic jam to move, $1/(1-p_{\text{s2s}})$ [16]. This outflow is the maximum flow achievable in the road [15]. Therefore, given that the speed in free-flow traffic is u_f, and from the fundamental relation (2), the maximum density in the free-flow section of the road is,

$$k_F = \frac{q_F}{u_f} = \frac{1-p_{\text{s2s}}}{U_{\max}-p_{\text{noise}}} \ . \tag{9}$$

Let the traffic jam region in Figure 2(b) be occupied by N_J vehicles spanning a length of L_J. Also, let the free-flow region have N_F vehicles in a distance of L_F. Then, the total length and number of vehicles are:

$$L = L_F + L_J \ , \tag{10}$$

$$N = N_F + N_J \ . \tag{11}$$

Using $k = N/L$, $k_F = N_F/L_F$, $k_{\text{jam}} = N_J/L_J$, equation (10) can be rewritten:

$$\frac{N}{k} = \frac{N_F}{k_F} + \frac{N_J}{k_{\text{jam}}} \; . \tag{12}$$

Substituting (11) into (12) yields,

$$\frac{N_F}{k_F} - \frac{N_F}{k_{\text{jam}}} = \frac{N}{k} - \frac{N}{N_J} \; . \tag{13}$$

Therefore, the fraction of vehicles in free-flow traffic is,

$$\frac{N_F}{N} = \frac{k_{\text{jam}} k^{-1} - 1}{k_{\text{jam}} k_F^{-1} - 1} \; . \tag{14}$$

Continuing from (10),

$$\begin{aligned} L_F &= L - \frac{N - N_F}{k_{\text{jam}}} \\ &= L - \frac{N}{k_{\text{jam}}} \left[1 - \frac{N_F}{N} \right] \; . \end{aligned} \tag{15}$$

Substituting (14) in (15) yields,

$$L_F = L - \frac{N}{k_{\text{jam}}} \left[1 - \frac{k_{\text{jam}} k^{-1} - 1}{k_{\text{jam}} k_F^{-1} - 1} \right] \; . \tag{16}$$

Hence, the fraction of the free-flow region is:

$$\frac{L_F}{L} = \frac{k_{\text{jam}} - k}{k_{\text{jam}} - k_F} \; . \tag{17}$$

Knowing that the MTR in the road must be equal to or higher than that of the free-flow region, then,

$$r_{c,L} \geq r_{c,L_F} \; . \tag{18}$$

Substituting (17) to (7), and using (18), the critical range for the entire road length, $r_{c,L}$, is given,

$$\begin{aligned} r_{c,L} &\geq \frac{\ln(L_F)}{k_F} \\ &= \frac{1}{k_F} \ln \left[\frac{L(k_{\text{jam}} - k)}{k_{\text{jam}} - k_F} \right] \qquad k > k_c \end{aligned} \tag{19}$$

The critical range, r_c, in (19) depends only on the length, L, of the road section and the vehicle density within the section, k, since both densities k_F and k_J are constants. The value of k_F is obtained from (9) using the values $U_{\text{max}} = 5$ cell/s, $p_{\text{noise}} = 0.01$, and $p_{\text{s2s}} = 0.5$,

$$k_F = \frac{1 - p_{\text{s2s}}}{U_{\text{max}} - p_{\text{noise}}} = \frac{0.5}{5 - 0.01} \approx 0.1 \; . \tag{20}$$

Finally, from equations (7) and (19), the lower-bound of the MTR in a highway of length L and density k is given by

$$r_c(k) = \begin{cases} \dfrac{\ln(L)}{k} & k \leq k_c \\[2ex] \dfrac{\ln(L)}{k_F} + \dfrac{1}{k_F} \ln \left(\dfrac{k_{\text{jam}} - k}{k_{\text{jam}} - k_F} \right) & k > k_c \end{cases} \tag{21}$$

Figure 3 shows the plot of equation (21). The values of k_c and k_F are determined for different values of U_{max} using (3) and (9), respectively.

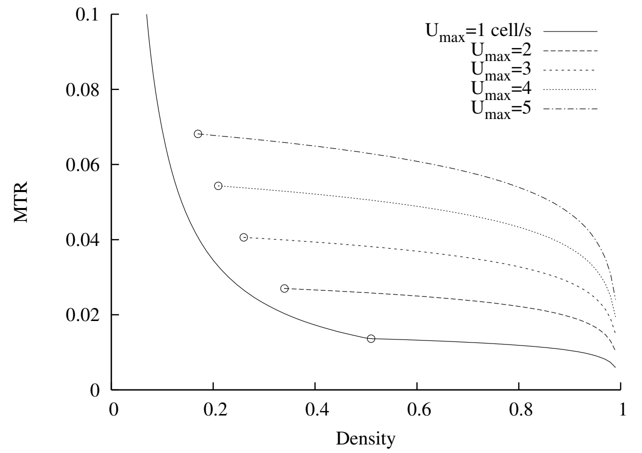


Fig. 3. The lower bound of MTR in a highway of 1000-cell length and various values of maximum speed, U_{max}.

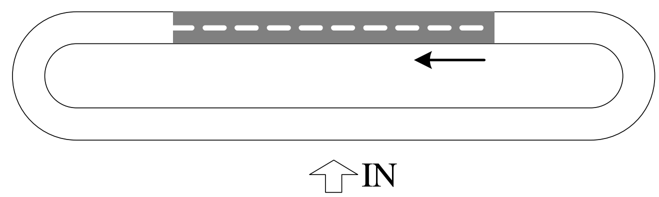


Fig. 4. Racetrack configuration.

V. Simulation evaluation

The analytical relationships that were derived in the previous section are verified through simulations of vehicle traffic. A closed-loop (racetrack) highway, with single or three lane(s), is used for all the simulations described in this section. The racetrack is 7.5 km long; vehicles enter from a parking facility with an input flow of 60 veh/hr and continue to travel around the track indefinitely, which causes vehicle density to increase until the jam density is reached and no more vehicles can enter.

In single-lane roads with no overtaking, vehicles will travel at the speed of the slowest vehicle regardless of their maximum speed capabilities. Therefore, all vehicles are assigned the same maximum speed (5 cell/s) in simulations of the single-lane highway while the three-lane highway configuration includes vehicles of various maximum speeds (3, 4, and 5 cell/s). Note that the maximum speeds are meaningful only in free-flow traffic. At higher densities, vehicles travel at a lower speed, which is unrelated to their maximum speed.

Simulation data was collected in a section of 1005-metre long in the middle of a highway (the shaded area in Figure 4). This section is located at the furthest point from the vehicle entry point in order to avoid the effect of the latter on the traffic. Each of the simulation experiments was executed 20 times.

The VANET within the measurement area is represented as a graph $G(V, E)$, where a set of vertices V represents vehicles, and a set of edges E represents direct communication links. In the simple communication model that is used here, a communication link, $e_{i,j} = (v_i, v_j)$ exists if and only if the Euclidean distance between vehicles v_i and v_j is less than or equal to the shortest transmission range between them, i.e,

$$E = \{(v_i, v_j) \in V^2 \mid |x_i - x_j| \le \min(r_i, r_j)\} \quad (22)$$

where x_i, r_i are the position and transmission range of the node v_i, respectively. Equation (22) results in an undirected graph.

Simulations were used to determine the MTR needed to connect the wireless network among vehicles in the road configurations described at the beginning of Section V. In general, the MTR is determined by constructing a MST in the graph $G(V, E)$ among the vehicles using Prim's algorithm. The MTR is the longest edge in the MST [6]. In a single-lane VANET, the MTR is the widest gap between any two consecutive vehicles. The MTR was determined in every simulation time-step and stored along with the vehicle density.

Figure 5(a) shows a scatter plot of MTR values vs. density in a single-lane VANET. The plot shows clearly that the MTR values are concentrated above the derived lower bound of equation (21) in densities above the critical density. However, MTR values drop below this bound to that of equation (7) at much higher densities indicating the return to the homogeneous distribution of vehicles as traffic jams increase in size and merge to become a wide traffic jam [13].

The data collected from the simulations is classified into 100 density intervals that cover the entire density range. The mean and the standard deviation of the MTR values are calculated within each density interval to be plotted vs. the average density in each interval. The shaded region in Figure 5(b) shows the mean value of MTR$\pm$the standard deviation vs. density in the single-lane road configuration. It is observed from the plot that the MTR values are higher than what would be the case in homogeneous traffic at densities above the critical density. The discrepancy starts at density ($k_c \approx 1/(U_{\text{max}} + 1) = 1/6$) when traffic is no longer in free flow. As a result, a longer MTR is needed to maintain the network connectivity in traffic conditions that exhibit mixed state of free-flow and traffic jams.

As density increases, traffic jams increase in size and merge with other traffic jams until the entire road is composed of one wide traffic jam. Consequently, the MTR decreases until it reach its minimum value of $1/k_{\text{jam}}$ (the distance from front-bumper to front-bumper between two vehicles).

The plot of the average maximum MTR is compared with two relations. The maximum transmission range, r_{max}, for a network of finite length, L, is obtained by assuming that all but one vehicle are packed at distance of $1/k_{\text{jam}}$ from each other at one side of the road while the remaining vehicle is located at the opposite side; thus the longest possible transmission range, r_{max}, is needed to preserve the network's connectivity. This range is:

$$r_{\text{max}} = L\left(1 - \frac{k}{k_{\text{jam}}}\right) + \frac{1}{k_{\text{jam}}} \ . \quad (23)$$

In addition, the graph in Figure 5(b) shows that the average upper bound MTR can be approximated by shifting the upper bound estimated in [9] higher by a factor, αL,

$$r_c \le \sqrt{L \ln(L)/k} + \alpha L \ , \quad (24)$$

where $\alpha = 0.25$. The proximity of the MTR to the upper bound estimate of (24) declines as the densities increases beyond the intersection point between (23) and (24) where the MTR declines rapidly towards the minimum value of $1/k_{\text{jam}}$.

Traffic jams continue to affect traffic in multi-lane roads as discussed previously. Recall that the density is expressed by the number of vehicles that occupy a unit distance per lane. As a result, the number of vehicles in a unit distance of a three-lane road is three times that of a single-lane road. Since more vehicles are packed in the same distance, the MTR needed in a multi-lane is less that of a single-lane of the same density value. As a result, Figure 6(a) shows that the lower bound for the MTR is reduced by a factor of three (which is equal to the number of lanes). Figure 6(b) shows an increase in the mean MTR value near the critical density, which is located at $k \approx \frac{1}{5}$ due to the lower average free-flow speed. The average maximum MTR can be approximated by (23) with $\alpha = 0$.

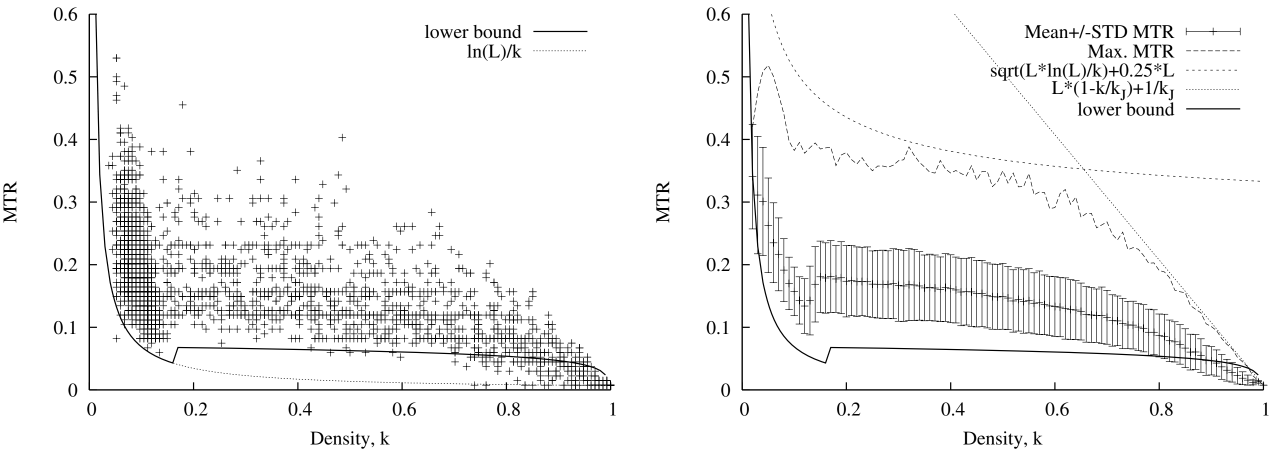
Note that equation (21) is developed for one-lane highway (one-dimensional VANET). As the number of lanes increases, the vertical distance between vehicles (at the same horizontal positions but between different lanes) becomes a factor in determining the MTR. In other words, the network becomes two-dimensional as the number of lanes increases. The study of this type of network is outside the scope of this paper.

VI. Summary and Conclusions

This paper provides a link between the phenomenon of traffic jams and the connectivity of a Vehicular Ad Hoc Network (VANET). The non-homogeneous distribution of vehicles due to traffic jams results in the need for a higher transmission range than what would be the case of the homogeneous distribution.

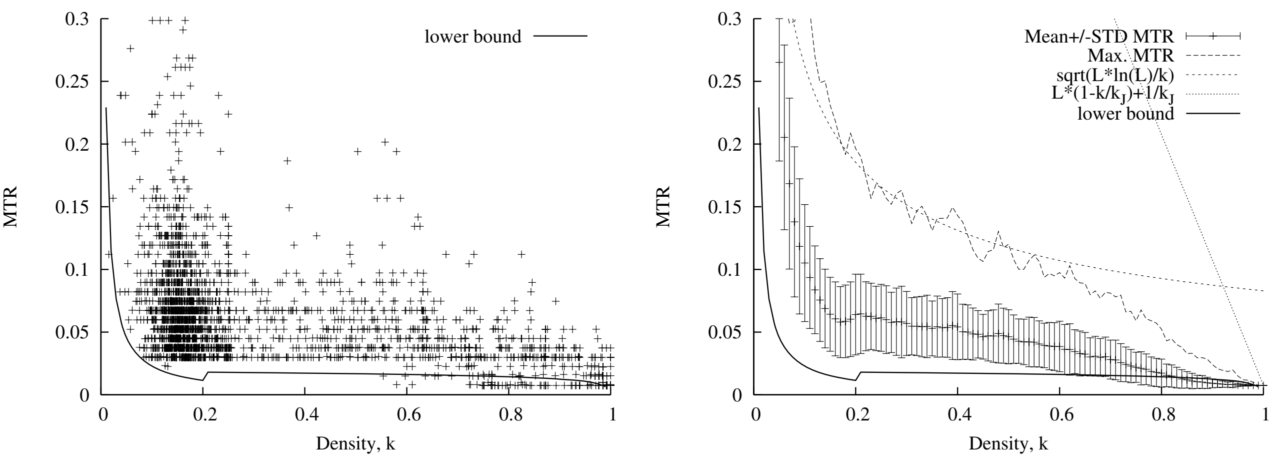
The main contribution of this paper in this regard is summarized in equation (21) where an analytical lower-bound for the Minimum Transmission Range (MTR) is derived. The relationship takes into account the non-homogeneous distribution of vehicles at densities beyond the free-flow densities. The new lower-bound shows that the increase in MTR can reach up to six times the value obtained from (7), which assumes homogeneous distribution, at density $k \approx 0.8k_{\text{jam}}$.

Simulation results show that the lower bound for MTR values can be estimated accurately for low and moderate densities. At high densities (near wide traffic jam conditions), vehicle distribution returns to the homogeneous phase; thus, the MTR values are lower than the estimates. The multi-lane scenario shows that MTR values are lower than those of a single-lane highway due to the additional number of vehicles on the highway for the same density-per-lane value.



a) b)

Fig. 5. MTR in a single-lane road.



a) b)

Fig. 6. MTR in three-lane road.

This observation implies that the presence of multiple lanes improves connectivity by lowering the MTR requirements.

REFERENCES

[1] P. Santi, "Topology control in wireless ad hoc and sensor networks," *ACM Comput.Surv.*, vol. 37, no. 2, pp. 164–194, 2005.

[2] O. Dousse, P. Thiran, and M. Hasler, "Connectivity in ad-hoc and hybrid networks," in *Proc. Twenty-First Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM'02)*, vol. 2, 2002, pp. 1079–1088.

[3] T. Nagatani, "The physics of traffic jams," *Reports on Progress in Physics*, vol. 65, no. 9, pp. 1331–1386, 2002.

[4] K. Nagel and M. Schreckenberg, "A cellular automaton model for freeway traffic," *Journal de Physique I France*, vol. 2, pp. 2221–2229, Dec. 1992.

[5] M. M. Artimy, W. Robertson, and W. J. Phillips, "Vehicle traffic microsimulator for ad hoc networks research," in *Proc. International Workshop on Wireless Ad-hoc Networks (IWWAN'04)*, Oulu, Finland, May 2004, pp. 105–109.

[6] M. D. Penrose, "The longest edge of the random minimal spanning tree," *The Annals of Applied Probability*, vol. 7, no. 2, pp. 340–361, May 1997.

[7] J. Díaz, M. D. Penrose, J. Petit, and M. Serna, "Convergence theorems for some layout measures on random lattice and random geometric graphs," *Combinatorics, Probability and Computing*, vol. 9, no. 6, pp. 489–511, 2000.

[8] P. Piret, "On the connectivity of radio networks," *IEEE Transactions on Information Theory*, vol. 37, no. 5, pp. 1490–1492, Sept. 1991.

[9] P. Santi and D. M. Blough, "An evaluation of connectivity in mobile wireless ad hoc networks," in *Proc. International Conference on Dependable Systems and Networks*, June 2002, pp. 89–98.

[10] Y. C. Cheng and T. G. Robertazzi, "Critical connectivity phenomena in multihop radio models," *IEEE Transactions on Communications*, vol. 37, no. 7, pp. 770–777, 1989.

[11] M. Desai and D. Manjunath, "On the connectivity in finite ad hoc networks," *Communications Letters, IEEE*, vol. 6, no. 10, pp. 437–439, 2002.

[12] H. Füßler, M. Mauve, H. Hartenstein, D. Vollmer, and M. Käsemann, "A comparison of routing strategies in vehicular ad-hoc networks," in *Reihe Informatik*, Mar. 2002.

[13] D. Jost and K. Nagel, "Probabilistic traffic flow breakdown in stochastic car following models," *Transportation Research Record*, vol. 1852, pp. 152–158, 2003.

[14] M. J. Cassidy, "Traffic flow and capacity," in *Handbook of Transportation Science*, 2nd ed., R. W. Hall, Ed. USA: Kluwer Academic Publishers, 2003, ch. 6, pp. 155–191.

[15] K. Nagel and M. Paczuski, "Emergent traffic jams," *Physical Review E*, vol. 51, pp. 2909–2918, 1995.

[16] R. Barlovic, L. Santen, A. Schadschneider, and M. Schreckenberg, "Metastable states in cellular automata for traffic flow," *The European Physical Journal B - Condensed Matter*, vol. 5, no. 3, pp. 793–800, Oct. 1998.