Urban Mobility Models for VANETs

Atulya Mahajan, Niranjan Potnis, Kartik Gopalan and An-I A. Wang
Computer Science, Florida State University
{mahajan,potnis,kartik,awang}@cs.fsu.edu

***Abstract*— Mobility models, or the movement patterns of nodes communicating wirelessly, play a vital role in the simulation-based evaluation of Vehicular Ad Hoc Networks (VANETs). Although recent research has developed models that better correspond to real world mobility, we still have a limited understanding of the level of the required level of mobility details for modeling and simulating VANETs. In this work, we examine a set of step-by-step enhancements to the level of details in mobility models for VANETs and evaluate the sensitivity of simulation results toward those modeling details. Through this process, we develop several new mobility models, that account for vehicular movement constraints such as traffic lights, multilane roads, and acceleration/deceleration. Using real and controlled synthetic maps, we compare our mobility models and two prior models. Our results demonstrate that the delivery ratio and packet delays in VANETs are more sensitive to the clustering effect of vehicles waiting at intersections and acceleration/deceleration of vehicles. We also found that the simulation of multiple lanes and synchronization at traffic signals have only a marginal impact on the ad hoc routing performance. Our work provides a sound starting point for further understanding and development of more realistic and accurate mobility models for VANET simulations.**

I. Introduction

Vehicular Ad Hoc Networks (VANETs) are a special case of Mobile Ad Hoc Networks (MANETs) and consist of a number of vehicles traveling on urban streets, capable of communicating with each other without a fixed infrastructure. VANETs are expected to benefit safety applications, gathering and disseminating real-time traffic congestion and routing information, sharing of wireless channels for mobile applications etc. One key component of VANET simulations is the movement pattern of vehicles, also called the *mobility model*. Mobility models determine the location of nodes in the topology at any given instant, which strongly affects network connectivity and throughput. The current mobility models used in popular wireless simulators such as NS-2 [2] tend to ignore real-world constraints such as street layouts and traffic signs. Consequently, the simulation results are unlikely to reflect the protocol performance in the real world.

For example, the widely used Random-Waypoint Model (RWM) [15] assumes that nodes move in an open field without obstructions. In contrast, the layout of roads, intersections with traffic signals, buildings, and other obstacles in urban settings constrain vehicular movement. In response to the limitations of RWM, more researchers have become interested in modeling 'realistic' mobility patterns for VANETs [11], [18], [23], [19], [9], [14], [12], [21]. Although these studies capture different levels of simulation details and realism, existing research has shed little light on the level of details required and the sensitivity of those details in simulation results of VANETs. Excessive details only prolong the running time of a simulation, while too few details will lead to inaccurate simulation results.

This paper addresses the following question: *what is the sensitivity of VANET simulation results toward individual mobility characteristics?* We identify constraints that significantly impact the performance of routing protocols in VANETs. As a complementary result, we also identify constraints that only marginally affect the routing protocol performance and could potentially be ignored. Our specific contributions are as follows:

- We introduce several new models that capture vehicular mobility at various levels of detail – the Stop Sign Model (SSM), the Probabilistic Traffic Sign Model (PTSM), and the Traffic Light Model (TLM). The focus of this paper is not to advocate one model over the other, but to use them to gain better insights into mobility models.
- We compared our mobility models with two prior models - the Random-Waypoint Model [15] and the Rice University Model (RUM) [18]. These models are evaluated over various parameters such as topology (real maps and controlled grids), vehicular speed, and the wait times at intersections.
- We show that one factor that significantly affects the performance of VANETs is the clustering effect of vehicles at intersections. Increasing either the wait times at the intersections or the number of nodes lead to increased clustering. Consequently, increased clustering leads to higher delivery ratios when neighboring intersections are within the transmission range and to lower delivery ratios when neighboring intersections are beyond the transmission range.
- We evaluate the roles of other factors that significantly impact VANET performance, including the topology (block sizes and road layouts) and acceleration-deceleration of vehicles
- We showed that for typical VANET experimental settings, adding complexity to the models, such as by simulation of multiple lanes and synchronization of traffic lights, yields limited impact on VANET performance.

II. Urban Vehicular Mobility Modeling

In this section we describe several new mobility models. Each successive model captures vehicular movement characteristics in increasing levels of detail. These models are based on real street maps extracted from the US censor bureau TIGER database [4]. The database also provides information about the road type and implicit information on speed limit and number of lanes (inter state highways, residential areas, etc). All roads are modeled as bidirectional roads. The SSM and PTSM assume a single lane in each direction of every road, whereas TLM provides the option for modeling multiple lanes.

A. Factors Affecting Mobility in VANETs

The mobility pattern of nodes in a VANET influences the route discovery, maintenance, reconstruction, consistency and caching mechanisms. Static or slow-moving nodes tend to dampen the changes in topology and routing by acting as stable relaying points for packets to/from the neighboring nodes. On the other hand, highly mobile nodes add entropy to the system and cause frequent route churn and packet losses.

Street Layouts: Streets force nodes to confine their movements to well-defined paths. This constrained movement pattern determines the spatial distribution of nodes and their connectivity. Streets can have either single or multiple lanes and can allow either one-way or two-way traffic.

Block size: A city block can be considered the smallest area surrounded by streets. The block size determines the number of intersections in the area, which in turn determines the frequency with which a vehicle stops. It also determines whether nodes at neighboring intersections can hear each other's radio transmission. Larger block sizes make the network more sensitive to clustering and degrade performance.

Traffic control mechanisms: The most common traffic control mechanisms at intersections are stop signs and traffic lights. These mechanisms result in the formation of clusters and queues of vehicles at intersections and subsequent reduction of their average speed of movement. Reduced mobility implies more static nodes and slower rates of route changes in the network. On the other hand, cluster formation can also adversely affect network performance with increased wireless channel contention and longer network partitions.

Interdependent vehicular motion: Movement of every vehicle is influenced by the movement pattern of its surrounding vehicles. For example, a vehicle would try to maintain a minimum distance from the one in front of it, increase or decrease its speed, and may change to another lane.

Average speed: The speed of the vehicle determines how quickly its position changes, which in turn determines the rate of network topology change. The speed limit of each road also directly affects the average speed of vehicles and how often the existing routes are broken or new routes are established. Additionally, acceleration/deceleration of vehicles and the topology of the map also directly affect the average speed of vehicles – if a map has fewer intersections, the vehicles are able to accelerate to higher speeds when compared to maps with many intersections and smaller block sizes.

B. Stop Sign Model (SSM)

In the Stop Sign Model (SSM), every street at an intersection has a stop sign. Any vehicle approaching the intersection must stop at the signal for a specified time (which is configurable). We used a default value of 3 seconds in our experiments. On the road, each vehicle's motion is constrained by the vehicle in front of it. That is – a vehicle moving on a road cannot move further than the vehicle that is moving in front of it, unless it is a multi-lane road and the vehicles are allowed to overtake each other. When vehicles follow each other to a stop sign, they form a per-street queue at the intersection. Each vehicle waits for at least the required wait time once it gets to the head of the intersection after other vehicles ahead in the queue clear up. Vehicle crossings at the intersection is not coordinated among different directions. Although an urban layout is unlikely to have stop signs at every intersection, this model does serve as a simple first step to understanding the dynamics of mobility and its effect on routing performance.

C. Probabilistic Traffic Sign Model (PTSM)

Next, we refined SSM further by replacing stop signs with traffic signals at intersections. In general, vehicles stop at red signals and drive through green signals. Although it is possible to simulate the detailed coordination of traffic lights from various directions, we did not implement it at this stage. We first wanted to understand whether such levels of detail would produce any significant impact on routing protocol performance.

As an intermediate step, we developed the Probabilistic Traffic Sign Model (PTSM). PTSM approximates the operation of traffic signs by not coordinating among different directions. When a node reaches an intersection with an empty queue, it stops at the signal with a probability p and crosses the signal with a probability $(1 - p)$. If it decides to wait, the amount of wait time is randomly chosen between 0 and w seconds. Any node that arrives later at a non-empty queue will have to wait for the remaining wait time of the previous node plus one second. The additional one second simulates the startup delay between queued cars. Whenever the signal turns green, the vehicles begin to cross the signal at intervals of one second, until the queue becomes empty. The next vehicle that arrives at the head of an empty queue again makes a decision on whether to stop with a probability p and so on. Similar to SSM, there is no coordination among vehicles crossing an intersection from different directions. This model avoids excessive stoppings, as in the case of SSM, and at the same time, approximates the behavior of traffic lights.

D. Traffic Light Model (TLM)

SSM and PTSM are highly approximate models of the behavior of vehicular traffic. In order to understand which other level of detail besides street topology is absolutely essential, we refined PTSM described earlier with successively greater levels of mobility details. We call this new model, the Traffic Light model (TLM).

Coordinated traffic lights:: Under TLM, traffic lights at each intersection are coordinated. First, consider an intersection with an even number of roads with single-lane opposing traffic. The lights turn green in such a manner that only traffic along a single pair of opposing sides cross the intersection simultaneously. Vehicles that need to turn left or right follow the free turn rule once they reach the head of the queue. While the traffic across one pair of opposing roads has the green signal, the remaining have red signal. After a fixed period, green signals are rotated to another pair of roads with opposing traffic. The case of an odd number of roads meeting at an intersection (such as a T intersection) is treated by permitting one of the roads to periodically have a green light by itself. This feature provides more coordinated traffic behavior compared to PTSM.

Acceleration and Deceleration:: The next level of detail we added to TLM was the acceleration and deceleration of vehicles. In this feature, vehicles at rest do not change their state to peak speeds instantaneously. Instead, they accelerate gradually from rest up to the maximum possible speed. Similarly, when approaching a stop sign or red light, they decelerate gradually to a stop.

Multiple Lanes:: Another feature of the TLM is the introduction of multiple lanes. For real maps, the number of lanes can be determined by the type of the road specified in the TIGER database. When a vehicle enters a new road, such as when crossing or turning at an intersection, it selects that lane in the new road which has the least number of vehicles (both moving and stopped).

Generating Variants of TLM:: The primary goal of our study is understand the sensitivity of mobility details on VANET performance, and to determine the details that are worth being included in a mobility model. For this purpose, various features in the TLM can be independently enabled or disabled to obtain different variants of TLM. In particular, four variants of TLM can be obtained by enabling or disabling the acceleration/deceleration and multi-lane features. Hence, the basic TLM without either of the two features has one additional feature over PTSM, namely coordinated traffic lights.

E. Implementation of Mobility Models

We implemented these mobility models in C++ as independent programs that generated mobility files. These mobility files serve as input to the wireless simulations in NS2. The initial vehicle positions and their destinations are chosen randomly. Each node follows the shortest path through the roads to its destinations. Upon reaching a destination, the node begins its journey to another random destination along the shortest path computed using the Dijkstra's algorithm.

Each model takes a time parameter (in seconds). For SSM, the time parameter denotes the duration each vehicle to stop at intersections. For PTSM, this parameter denotes the maximum duration for each vehicle to stop at at the head of empty intersections. For TLM, this parameter represents the duration of green lights for each opposing pair of roads at an intersection. The street topology is specified in a file that stores the road identifiers and the starting and ending road coordinates. In SSM and PTSM, vehicles always travel within 5 miles/hour of the street speed limit. TLM has a slightly different mechanism with vehicles accelerating from rest to reach the speed limit, and then decelerating to stops. The acceleration and deceleration rates were 3 meter/second^2.

Parameter	Default Value(s)
Simulation Time	900s (plus 450s warmup)
Routing Protocol	AODV
NS2 Version	ns 2.28
Transmission Range	250m
Number of Nodes	100
CBR Sources	15 sources and sinks at 4 pkts/sec and 64 byte pkt
Mobility Models	RWM, RUM, SSM, PTSM, TLM
Topologies	1200 $\times$ 1200m Grid, Real Map
Max. Wait Time	SSM–3 sec PTSM–30 sec ($p = 0.5$) TLM – 30 sec
Max. Node Speed	35 mph
Accel./Decel. Rate	3 meters/sec^2 for TLM
Performance Metrics	Delivery Ratio End to End delay Mobility, Clustering

TABLE I
NS2 WIRELESS SIMULATION PARAMETERS

III. PERFORMANCE EVALUATIONS

We used the NS-2 network simulator [2] to evaluate various mobility details on the AODV ad hoc routing protocol. Table I summarizes the default values of the various simulation parameters. We compared SSM, PTSM, TLM, the Random Waypoint Model (RWM) [15] and the Rice University Model (RUM) [18]. RWM captures mobility in an open field with no obstacles, roads, or intersections. RUM simulates roads in a real map, but vehicles do not stop at intersections. For controlled experiments, we varied the block sizes in a grid topology over a 1200m $\times$ 1200m area. We also used several real world street maps extracted from the US Census Bureau TIGER [4] database. Although real world maps are useful in understanding the combined effects of various modeling details, we also used a controlled grid topology to study isolated effects of block sizes. Each experiment lasted 900 seconds, with an additional 450-second warm-up period. Experiments were repeated with at least five separate mobility patterns to attain a 95% confidence interval.

A. Varying Number of Nodes

This section compares various mobility models with different numbers of nodes in a a $1200m \times 1200m$ grid topology with a block size of $200m \times 50m$. Figures 1 and 2 compare the delivery ratio and end-to-end delay among all mobility models. SSM had a wait time of 3 seconds. PTSM had a maximum wait time of 30 seconds. TLM switched signals with a periodicity of 30 seconds and used two lanes in each direction with acceleration/deceleration of vehicles enabled.

The results indicated that the RWM yields the lowest delivery ratio and the maximum end-to-end delay, for this particular topology. The range of performance variation across various models highlights our point regarding the importance of fidelity of mobility models in VANET simulations.

The common trend is that the delivery ratio increases with the number of nodes, up to 100 nodes, as the connectivity of the communication graph increases. Then the delivery ratio starts decreasing as the number of nodes increases further. This behavior is due to the increased channel contention as the large number of nodes leads to a flood of control messages in the network. The end-to-end delay in Figure 2 displays the opposite trend: it first decreases as the number of

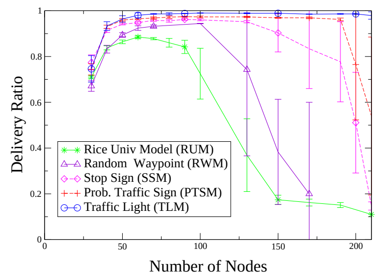

Fig. 1. Delivery ratio vs. number of simulated nodes.

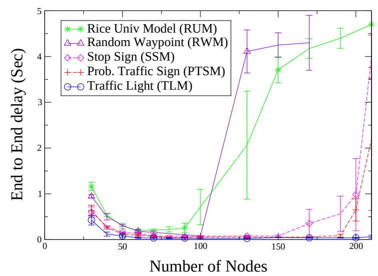

Fig. 2. End-to-end delay vs. number of simulated nodes.

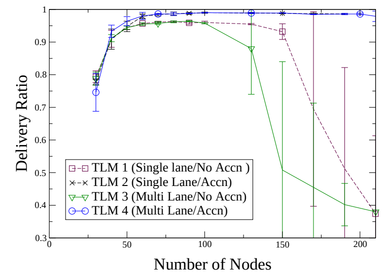

Fig. 3. Delivery ratio vs. number of simulated nodes for different versions of the traffic light model.

nodes increases, and then there is a sharp increase thereafter. We also experienced certain NS2 constraints as the number of nodes increased. The simulation time became a concern because we needed to explore a large parameter space. Also, the resource requirements of memory and storage (for output traces) became prohibitive. Additionally, with a large number of nodes, the confidence intervals of performance numbers widen significantly, further requiring more repetitions to reduce the variance of the results. Unless specified, we used 100 nodes for simulations in the remaining evaluations.

To understand the sensitivity of various mobility features (e.g. multilane roads and acceleration/deceleration of vehicles), we repeated the same experiment on TLM, with combinations of features enabled/disabled (Figures 3 and 4) compare the performance of the resulting four variants. The results indicate that acceleration/deceleration led to a significant increase in the delivery ratio because this feature reduces the average speed of vehicles. Thus, network routes are more stable. Additionally, the performance difference between the single-lane and multilane models is not noticeable below 100 nodes. However, with acceleration/deceleration disabled, it becomes noticeable beyond 100 nodes as the channel contention begins to rise. It is interesting to note that, once the acceleration/deceleration is enabled, the difference between the single-lane and multi-lane models becomes negligible. At first glance, multiple lanes without acceleration and deceleration differ from single lanes without acceleration and deceleration. However, the confidence interval is rather wide. After checking the average vehicle speed (Figure 15), and the average percentage of nodes moving at a given time (Figure 10), the two models appear to have the same clustering effects at intersections with cars moving at a similar average speed. Therefore, we believe that the difference is largely within margins of statistical errors. Thus, with our experimental settings of having fewer than 200 nodes in a 1200m x 1200m area (which is very typical), the additional complexity of modeling multiple lanes will not significantly affect the performance of VANETs.

B. Varying Number of CBR Sources

This section presents the delivery ratio and packet delay with varying Constant Bit Rate (CBR) sources. We used a $1200m \times 1200m$ grid topology with a block size of $200m \times 50m$. The number of nodes was fixed at 100. Figures 5 and 6 show that when the number of sources increases beyond 15, there is an increase in the end-to-end delay by an order of magnitude and a significant drop in the delivery ratio. The deviation in results is also quite large beyond 15 sources, as indicated by the confidence intervals. When the number of CBR sources increases, there is an increase in the number of packets contending for a common wireless channel, which leads to more collisions and packet drops. In the remaining experiments, we use 15 CBR sources among 100 nodes.

C. Varying Vehicle Speeds

We varied the maximum speed limit of vehicles and analyzed the performance for various mobility models (Figure 7). Note that the maximum speed is based on the type of road, as defined by the Census Bureau. For example, a type x road has a speed of 25 mph, whereas a type y road has a speed of 35 mph. We varied the speed from its default value to study how this parameter affects the resulting mobility pattern. The results show that under realistic settings (e.g. maximum speed limits $\leq$ 45 mph) different mobility models are within 5

D. Varying Maximum Wait Times at Intersections

To further understand the effect of vehicles stopping at intersections, we varied the maximum wait time of nodes at intersections (Figure 8). The delivery ratio results brought out an interesting aspect of this study. As expected, the RUM model yields the lowest delivery ratio due to its highly dynamic pattern of mobility. However, in contrast to our earlier experiments, SSM yields a higher delivery ratio compared to PTSM. The reason is that SSM results in a more static network than PTSM does, where nodes are forced to stop at all intersections. On the other hand, PTSM nodes at intersections decide with a 50no acceleration/deceleration TLM displays a marginally lower delivery ratio than PTSM for the same wait time because coordinated traffic lights provide a slightly higher rate of churn compared to PTSM.. However, the addition of multiple lanes and acceleration/deceleration to TLM yields the highest delivery ratio among these models. This result, combined with our earlier observation about negligible impact of modeling multiple lanes, suggests that the introduction of acceleration/deceleration effectively slows down the vehicle speeds most significantly and dampens the changes in the network topology. However, these results are also dependent upon other factors, such as block sizes, which we will consider next.

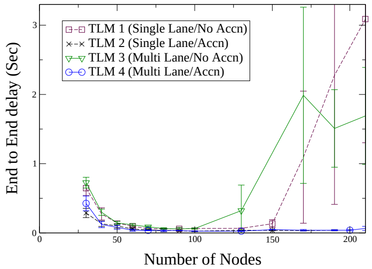

Fig. 4. End-to-end delay vs. number of simulated nodes for different versions of the traffic light model.

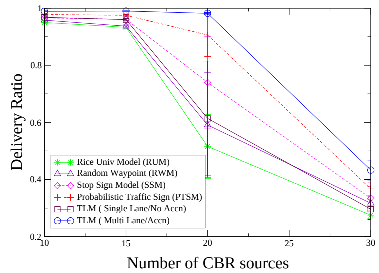

Fig. 5. Delivery ratio vs. number of CBR sources.

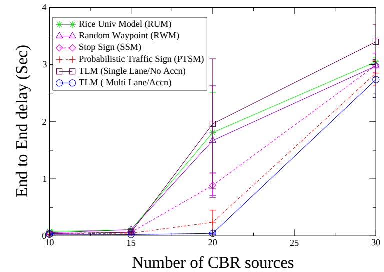

Fig. 6. End-to-end delay vs. number of CBR sources.

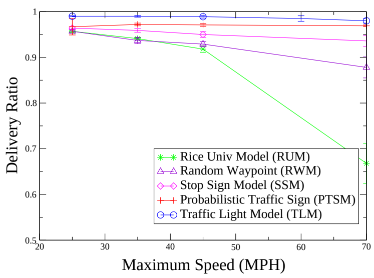

Fig. 7. Delivery ratio vs. maximum speed of vehicles.

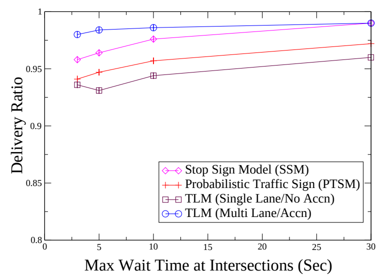

Fig. 8. Delivery ratio vs. maximum wait time at intersections.

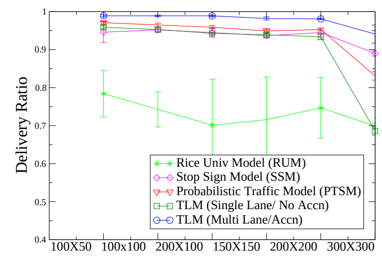

Fig. 9. Delivery ratio vs. increase in block size.

E. Effect of Block Sizes

The block sizes in the topology play an important role in determining the performance of VANETs. With large block sizes, vehicles spend more time in traversing between intersections; thus, nodes are mobile more often. This increased mobility leads to a weakened connectivity in the network, and a corresponding drop in the delivery ratio. To validate this hypothesis, we conducted experiments with varying block sizes in a $1200m \times 1200m$ area. Figure 9 largely confirmed our hypothesis – as the block size increases, the delivery ratio decreases. The RUM model is not sensitive to block sizes, since nodes do not stop at intersections. With the largest evaluated block, SSM outperforms PTSM due to a lower churn rate of routes, illustrating the interplay between block sizes and wait times in VANET simulations.

F. Analysis of Increased Mobility

The results of our experiments showed a distinct trend between the performance of various mobility models -TLM resulted in the highest delivery ratios, and the performance did not degrade considerably with an increase in the number of simulated nodes; PTSM showed a higher delivery ratio than SSM, and the throughput obtained through use of these models was considerably higher than RUM. This brings into context our hypothesis that varying the degree of mobility (node speed) within these networks is the reason for differing performance. In SSM, each node is forced to stop at each intersection. On the other hand, PTSM nodes stop only at non-empty intersections and some of the empty intersections. However, the default wait times for PTSM are higher as compared to SSM. This leads to a network that is effectively more static when compared to SSM, with better connectivity and corresponding performance improvements. TLM eliminates the probabilistic behavior of traffic lights and introduces acceleration and deceleration of vehicles, which leads to an even more stable network. To gain a detailed understanding, we identified metrics that measured the mobility of the nodes and the clustering of vehicles at intersections. The first metric provided us with a measure of the fraction of nodes we expected to actually be mobile at any given instant. The second metric was the extent of clustering at intersections. The number of clusters of vehicles could be treated as an effective number of nodes in the network, since all the nodes in a cluster displayed similar connectivity to nodes outside the cluster. The third metric measured the average speed.

1) Average Number of Mobile Nodes: To compute this metric we determined the number of nodes that are not waiting in a queue at any intersection. We took samples each second, averaged the results over the entire simulated time, and represented the result as the percentage of total nodes.

The first observation is that for the same wait time, varying the number of nodes does not appear to affect the percentage of mobile nodes significantly. This implies that the topology and wait time are more influential to the percentage of moving nodes compared to the number of nodes, up to 400 nodes within a $1200m \times 1200m$ area. Under similar conditions of wait time and topology, SSM is less mobile when compared to PTSM as expected. The introduction of acceleration/deceleration of vehicles to TLM increases the percentage of moving nodes in the network significantly, as slower average speeds reduce the chance of nodes being queued at intersections. To illustrate the effect of the wait time, we also evaluated both PTSM and TLM with a similar value of the wait time. The plots indicate that for the same wait time of 10 seconds, PTSM is more mobile than SSM, with PTSM having an average of 85% of the nodes moving at any time compared to 68% for SSM.

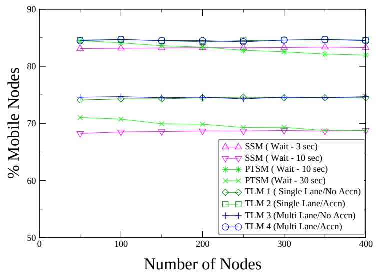

Fig. 10. Percentage of mobile nodes at a given time.

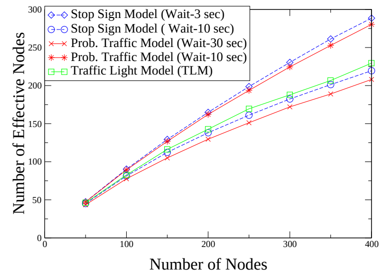

Fig. 11. Clustering Effect: Decreasing slope of plots indicates increased clustering.

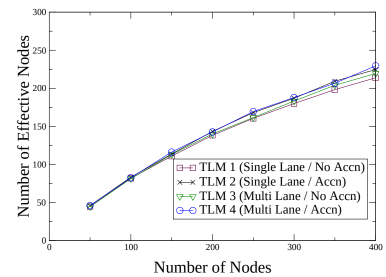

Fig. 12. Effective number of nodes for different variants of the TLM.

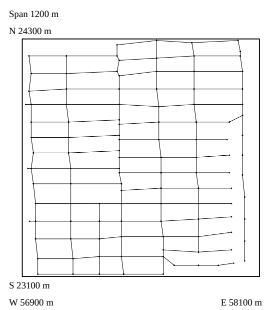

Fig. 13. Real world map – 1200 × 1200m, Houston, Texas – a subsection of the map used in[18].

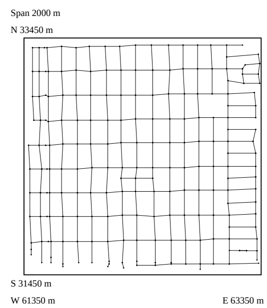

Fig. 14. Real world map – 2000m × 2000m, Tallahassee, Florida.

2) Average Number of Clusters: Stopping of nodes at intersections effectively creates many clusters all over the network. Connectivity among the nodes within a cluster is near perfect (minus the network contention effects). On the other hand, if one node in the cluster cannot reach a distant node outside the cluster, then most likely all nodes in the cluster are unable to reach the same distant node. The number of such clusters can be treated as the effective number of (logical) nodes in the VANET at any time. Thus, we postulate that clustering has an effect similar to decreasing the number of nodes in the network.

To estimate the number of effective nodes, we divided the topology into $60m \times 60m$ regions, counted the number of regions containing at least a node each second, and took the average. Figure 11 shows that when the number of nodes increases, the number of effective nodes grows sub-linearly as more nodes are clustered at intersections. TLM resulted in a marginally greater number of effective nodes as compared to PTSM, for a similar wait duration of 30 seconds. This indicates a reduced clustering effect in TLM – a consequence of the reduced average speeds of the vehicles. We also studied the variation of this effect with the maximum wait time at intersections. With a wait time of 10 seconds, we observed that SSM with a wait time of 3 seconds resulted in a similar value as that of PTSM, which is consistent with our findings in Figure 10. Interestingly, Figure 12 shows that acceleration/deceleration and multiple lanes do not significantly impact the difference in clustering level between the various versions of TLM. This indicates that the performance difference across TLM variants is mainly due to differences in average speed.

3) Average Speed of Vehicles: We computed the average speed for each vehicle as the ratio of the entire distance it travels during the simulation and the simulated time (Figure 15). We observed that PTSM results in lower average speeds compared to SSM, because of the longer wait times involved at intersections. For TLM variants, the addition of acceleration/deceleration leads to a significant decrease in average speed, which translates into higher delivery ratios. Also observe that TLM with multiple lanes does not noticeably affect the average speed compared to single lane.

G. Real Map Results

Having the insights into the various factors affecting VANET performance in grid topologies, we conducted experiments using real maps extracted from the TIGER database. We performed a set of experiments using a smaller section of the map used by RUM [18]. The original map was $2400m \times 2400m$, but the NS2 simulations at this size do not scale due to the large number of nodes required (or conversely, one needs to set unrealistic transmission ranges) to maintain meaningful delivery ratios. To address this problem, RUM [18] used a transmission range of 500 meters, which we considered to be too large for our settings. Hence, we decided to maintain the original default NS-2 setting of 250 meters transmission range, with a truncated map size of $1200m \times 1200m$. Figure 13 shows the map layout for this set of experiments. Fig 16 shows that the delivery ratio for each model increased with the number of nodes up to 100 nodes, followed by a rapid degradation in performance thereafter. However, the performance using TLM remained constant up to almost 200 nodes. These results reconfirm our understanding regarding the correlation between topology and mobility, and between the mobility and performance of the simulated VANETs.

For another experiment, we extracted a map of Tallahassee, over an area of $2000m \times 2000m$. The results in this case were different from what we had seen so far, owing to a much larger area as compared to the first map. Figures 14 and 17 present the actual map and the performance results. In this experiment, we were able to observe the effect of network partitioning due to the large area and the initial low density of nodes. This effect was also strengthened due to the stoppages enforced by our mobility models – once a node is in the waiting state at an intersection, it is highly likely to

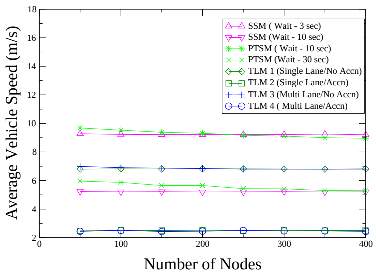

Fig. 15. Average speed for various models.

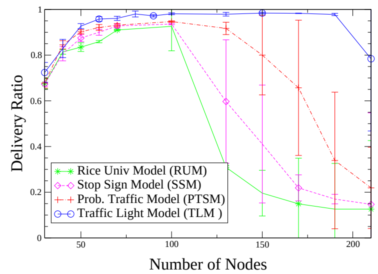

Fig. 16. Delivery ratio for map in Fig. 13.

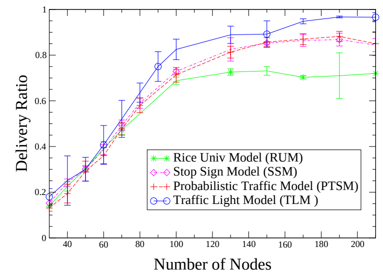

Fig. 17. Delivery ratio for map in Fig. 14.

communicate with other nodes in other intersections due to the large size of the map. The delivery ratios were initially very low with a small number of nodes, and the performance actually improved as the number of nodes was increased up to 200. This was in contrast to the results obtained with the smaller map, where the performance went down with an increase in the number of nodes, perceivably due to network saturation. This reinforces our observation that these simulation results must be analyzed with the topology in mind. However, our basic understanding remains valid. The delivery ratio with TLM still remains higher than that with PTSM, SSM, and RUM due to a lower network churn

IV. Related Work

A number of mobility models have been proposed for simulating wireless ad hoc networks in different scenarios, including VANETs. We summarize the most relevant ones. To the best of our knowledge, our work is the first systematic attempt to understand and evaluate various factors that affect mobility in VANETs and, consequently, impact the routing performance. In contrast to earlier works, the focus of our paper is not to recommend any mobility model, but to understand and evaluate the performance impact and significance of various mobility factors on VANET simulations

The most used mobility model in literature is the Random WayPoint (RWM) model [15]. Every node selects a random destination and speed and then moves to that destination with the chosen speed, pauses, and then moves again to another random destination. Other similar open-field models include the Random Walk, Random Direction Model and the Boundless Simulation Area Model [8]. Camp [8] observed that the spatial distribution of nodes in such models is toward the center of the simulation area. The nodes appear to converge and diverge repeatedly at the center, which leads to inherent flaws in simulations.

Davies [10] evaluated a number of representative mobility models for ad hoc networks. The authors concluded that none of the evaluated models depicted realistic mobility scenarios and there was a need to implement mobility models appropriate for the scenarios under consideration [23] reached a similar conclusion after evaluating many other mobility models. Other works [6], [17] have also attempted to improve RWM to make it more realistic, though not within the context of VANETs.

Most of the research mentioned target mobility modeling in general, but little work has been done toward mobility modeling specifically for VANETs. Bai [11] argued that the choice of mobility model can affect the performance of the MANET routing protocols, and introduced the Freeway and Manhattan mobility models, which simulate node mobility on roads specified through maps. The Freeway model attempted to model movement of vehicles on freeways. A map had several freeways having multiple lanes. Each vehicle's movement was restricted to its lane, and the velocity of nodes was dependent on their recent velocities. The Manhattan model captured an urban area similar to the grids that we have used in our experiments. Whenever a vehicle reached an intersection, it was determined with some fixed probability whether it would turn left or right, or continue on the same street. The vehicles were not constrained to pause, stop, or queue up at intersections.

Saha et al. [18] at Rice University modeled mobility of vehicles on real street maps, which were obtained from the TIGER database [4] maintained by the Census Bureau, by constraining vehicle mobility to street boundaries. Their model, which we call RUM in this paper, does not enforce any traffic rules on the network, especially at intersections. They showed that results obtained from RUM are similar to those obtained from the RWM. Because RUM is a good starting point toward modeling vehicular mobility, we included RUM as one of the base cases for performance comparisons.

Choffnes and Bustamante [9] recently introduced a vehicular mobility model for urban environments. With their simulators configured to generate delivery ratios between 0.05 and 0.3, they observed that the network performance in such a network was significantly different from the RWM. The authors also observed that the performance varied with the type of environment being simulated. Our evaluations confirmed their findings. Additionally, our evaluations in this paper used reasonable parameter settings to generate delivery ratios over 90% that are within the usable range. Because their mobility model is written using the SWANS simulator, we found it difficult to evaluate their mobility models without significant porting effort to NS2.

Work in [19] presents a mobility model that captures various effects of group mobility over large geographical areas, the target application being cellular networks. In the Reference Point Group Mobility model (RPGM) [13] every node has an individual component as well as a group component in the movement vector. Both the mobility components are based on RWM, the former within the group scope and latter within the entire arbitrary space. This is significantly different from vehicular motion on streets. Another group mobility model is evaluated in [5] typically for military scenarios involving movement of nodes in groups.

Random Trip Model [7] integrates several models including random way point model, random walk model, and city section model. For modeling mobility in cities, [14] proposed several theoretical models like city area, area zone, and unit street models. However, as pointed out in [10], these models lack specific details for actual node movement calculations. They also introduce considerable computational effort and complexity when used in simulations.

Some works in VANETs focus upon using mobility traces and/or proprietary software tools. In [12], a multi-tier ad hoc wireless routing architecture is proposed based on the collection of realistic mobility traces from city buses in metropolitan area. However these traces need not necessarily generalize mobility for all vehicles over varied topologies. Proprietary traffic simulation tools like Paramics [3] and CORSIM [1] are also available commercially for modeling modern transportation systems. For instance, [21] uses Paramics to generate node movements. However, apart from some synchronization overhead involved among traffic simulation and wireless simulation, use of proprietary software hinders further research and development. Additionally, most of these tools hide the topology details from the simulator.

Interest in VANETs and the performance of protocols at different layers has been increasing off late. For instance, [16] studies the protocol behavior at the MAC layer and proposes a new multihop broadcast protocol for realistic vehicular traffic scenarios. [21] modulates power level and transmission intervals to minimize packet collisions in inter-vehicular communication. In [20], the authors propose a mobility centric algorithm for data dissemination in vehicular networks. Performance evaluation of safety applications in VANETs over the dedicated short range communication (DSRC) standard have been performed in [22]. All of these optimizations and evaluations depend upon an in-depth understanding of the factors that impact mobility patterns and protocol performance in VANETs, which is our focus.

V. Conclusions

Mobility models play a critical role in accurate simulation of routing protocol performance in Vehicular Ad Hoc Networks (VANETs). In this paper, we have evaluated the sensitivity of mobility details on VANETs in an urban context. We proposed three new but related vehicular mobility models – the Stop Sign Model, the Traffic Sign Model, and the Traffic Light Model – that capture the movement pattern of vehicles in urban environments at varying levels of detail. Our results indicate that the clustering effect of vehicles waiting at intersections and acceleration/deceleration of vehicles are significant factors that affect the delivery ratio and packet delays in VANETs. Additionally, we found that the simulation of multiple lanes and coordinated traffic lights has only a marginal impact on the ad hoc routing performance. Though far from being the final word, our work provides a sound starting point for further understanding and development of mobility models for VANETs.

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