JOURNAL OF INFORMATION SCIENCE AND ENGINEERING 29, 985-1000 (2013)

DOI:10.1688/JISE.2013.29.5.11

Effects of Preferred Routes and Destinations on the Performance of Vehicular Network*

KUN-CHAN LAN, CHIEN-MING CHOU AND CHING-FANG YANG
Department of Computer Science and Information Engineering
National Cheng Kung University
Tainan, 701 Taiwan

Vehicular Ad-Hoc Networks (VANET), in which vehicles constitute the mobile nodes in the network, have attracted increasing interest in both academia and industry. However, due to the prohibitive cost of deploying and implementing such a system in the real world, most of the related research relies on simulations for evaluation purposes. A key component for VANET simulations is a realistic vehicular mobility model, as this ensures that the conclusions drawn from simulation experiments will carry through to the real deployments. Node mobility in a vehicular network is strongly affected by the driving behavior such as route choices. While route choice models have been extensively studied in the transportation community, as far as we know, the effects of preferred route and destination on vehicular network simulations have not been discussed much in the networking literature. In this work, we set out to understand the effect of route choices on vehicular network simulation. We also discuss how different destination selection models affect two practical ITS application scenarios: traffic monitoring and event broadcasting. We conclude that selecting a sufficient level of detail in the simulations, such as modeling of route choices, is critical for evaluating VANET protocol design.

Keywords: VANET, route choices, simulation, node distributions, traffic monitoring, event dissemination

1. INTRODUCTION

Vehicular Ad-Hoc Network (VANET) communication has recently become an increasingly popular research topic in the area of wireless networking, as well as in the automotive industry. The goal of VANET research is to develop a vehicular communication system to enable the quick and cost-efficient distribution of data for the benefit of passengers' safety and comfort.

While it is crucial to test and evaluate protocol implementations in a real world environment, simulations are still commonly used as a first step in the protocol development for VANET research. Several communication networking simulation tools already exist to provide a platform to test and evaluate network protocols, such as ns-2 [1], OPNET [2] and Qualnet [3]. However, these tools are designed to provide generic simulation scenarios, without being particularly tailored for applications in the transportation environment. In addition, simulations also play an important role in the field of transportation. A variety of simulation tools, such as PARAMICS [4], CORSIM [5] and VISSIM [6], have been developed to analyze transportation scenarios at the micro- and macroscale levels. However, to date there have been only few attempts [7, 8] to create commu-

Received February 12, 2011; revised August 1, 2011; accepted September 23, 2011.
Communicated by Wanjiun Liao.
* This research is supported by the National Science Council of Taiwan under the Contract No. NSC 99-2220-E-006-023 and NSC 100-2219-E-006-005.

nication scenarios in a realistic transportation simulation environment.

One of the most important parameters in simulating vehicular networks is the node mobility. It is important to use a realistic mobility model so that results from the simulation correctly reflect the real world performance of a VANET, as shown in some prior studies [7, 9]. Node mobility in a vehicular network is strongly affected by the drivers' behavior, which can change road traffic at different levels. Drivers' preferences in path and destination selection can further affect the overall network topology. It has been shown that drivers tend to use certain regular routes for their daily routines [10], and only 15.5% of commuters reported that they did not always choose the same exact route to work. Once a commuter has settled on a habitual route, the route choice strategies they deploy might possibly descend to a subconscious level, unless there are external factors (*e.g.*, accidents or traffic jams) that bring the choice of route back to the conscious level [11]. Furthermore, some commuters might select their routes based on the suggestions of some travel guidance system, such as variable message signs. Once a commuter has had a good experience with using a travel guidance system, they might increase their reliance on such advice the next time they travel [12]. While most current navigation systems use the shortest path to the destination for selecting routes, some commuters use faster paths instead of shorter ones to avoid congestion and reduce travel time. Some studies also show that path selection could possibly change on a temporal basis [13]. For example, when driving in the evening commuters usually have more flexibility in selecting alternate routes than when they drive to work in the morning.

In this paper, we set out to understand the effect of path selection (for a particular destination) and destination selection on vehicular network simulations. We also consider two application scenarios in which we assume cars are equipped with sensors and can collect road information. In the first scenario, we consider the situation in which some road-side units (RSUs) are deployed so that cars can push their sensor data online via the help of such units, which we assume are connected to servers on the Internet. In other words, each car can upload its sensor data to the Internet when it encounters a RSU. We also assume that the sensor data can be sent to a RSU even when it is far away if there exists a multi-hop path between the source and the RSU. In the second scenario, we consider the case in which cars want to disseminate their sensor information over the vehicular network via vehicle-to-vehicle communication only. The contributions of this paper are threefold: First, we demonstrate the importance of modeling route choice in vehicular simulations. Second, we first briefly discuss how different destination selection models affect network connectivity and cluster size. We then use simulations to demonstrate how the destination selection could potentially affect the performance of practical ITS applications. Finally, we show a destination selection model could have different effects on different ITS applications.

2. RELATED WORK

Details in the mobility model may have a critical effect on the fidelity, and thus the usefulness, of the resulting network simulations. Zhang *et al*. [14] used traces taken from the UMass DieselNet project to study the effect of mobility models on the performance of DTN. They showed that a finer-grained route-level model of inter-contact times is able to predict performance much more accurately than a coarser-grained all-bus-pairs aggregated model, which suggests caution should be taken in choosing the right level of detail when modeling vehicle mobility.

Random WayPoint (RWP) [15] is an earlier mobility model that has been widely used in Mobile Ad-hoc Network (MANET) simulations. RWP assumes that nodes can move freely in a simulation area, without considering any obstacles. RWP model fails to provide a steady state in that the average nodal speed consistently decreases over time [16], and its is inapplicable in VANET simulation since in a VANET environment vehicles are typically restricted by streets, traffic lights and obstacles. Treiber *et al.* [17] discussed a model that supports car turning at the intersections. Bai *et al.* [18] undertook a similar study, and further introduced Freeway and Manhattan mobility models in which car following and turning behaviors are included. However, unlike our study, none of these works considers the effect of traffic lights in their simulations.

Huang *et al*. [19] designed three model parameters: turn probability, road section speed and travel pattern to capture the regularity of the taxi mobility from GPS traces. Travel pattern depicts the regularity of long run trips based on travel grids from origination to destination for probability matrixes. However, to decide the size of the travel grid is challenging since a large size of the travel grid will merge different travel patterns and a small size of the travel gird cannot capture the characteristic of the travel pattern. Most of these prior work selected routes in their simulations based on random decisions and use the same routes throughout the simulation. In reality, drivers might have habitual routes from the source to the destination and change their routes from time to time to avoid congestion. Complementary to previous studies, in this paper we look at the effect of preferred routes on VANET simulations.

Many different route choice models have been proposed. For example, Dia and Panwai [20] used fuzzy logic to model the impact of traveler information system on route choices. Liu and Huang [21] investigated day-to-day route paths and modeled them with the logit-based stochastic user equilibrium state. In addition, Shenpei and Xinping [22] discussed how route choices are affected by signal split, while Zhao and Li [23] proposed a route choice model that considers human memory and traffic information factors. Guo *et al*. [24] proposed a path choice model based on game theory, and assumed that drivers obey traffic information to select their alternate routes. Dingus *et al*. [25] discussed how route choices are affected by human factors such as efficiency (*e.g.*, fastest route vs. shortest route), problem avoidance (*e.g*., safer routes) and road condition (*e.g.*, number of traffic lights). They showed a shortest path is not necessarily the driver's first choice when selecting routes, and that very often commuters use faster paths to avoid congestion and reduce travel time [26].

While there are a huge amount of works that model driving behavior in the transportation literature, there are only a few studies in the networking literature that described the impact of driving behavior on vehicular network simulations. For example, Fiore and Härri [27] simulated different mobility models and observed their effect on cluster size and link duration. Dressler and Sommer [8] evaluated route choice strategies via different route choices to show their impact on average speed. They did not consider the effect of route choice on the performance of network communication though.

3. SIMULATION ENVIRONMENT

To understand the effect of preferred route and destination on vehicular network simulation, we use MOVE [28] to simulate various driving behaviors. MOVE runs on top of an open-source micro-traffic simulator called SUMO [29]. MOVE also supports modeling obstacles on roads by allowing users to specify the shape of the obstacle and their penetration loss. We used Cramer's Rule [30] to check if there is an obstacle between the sender and the receiver and adjust the radio signal attenuation accordingly based on the obstacle's penetration loss. The roads in our simulations have two lanes and are bi-directional. Each simulation runs for 2,000 seconds and the maximum radio transmission range is 250m. We enabled CSMA/CA in our simulations and used the TwoRayGround model to simulate the radio propagation. All nodes employ 802.11 MAC operating at 2Mbps.

4. PREFERRED ROUTE AND DESTINATION

Mobility models play an important role in VANET simulations and driving behavior could strongly affect the mobility model. Since a truly realistic simulation is very challenging to produce, as human behavior and unexpected events are difficult if not impossible to model, simulation designers need to understand what level of detail is appropriate to the research questions they are examining. In this section, we discuss the effects of driving behavior on VANET simulations in two different cases, including path selection and destination selection.

4.1 Path Selection

Path selection is highly dependent on an individual's personal perceptions, experiences, preferences, and so on. The decision of path selection could have an effect on road congestion and clustering of vehicles. In this section, due to the space limitations of this paper, here we describe the effect of path selection with three examples: turning decisions at an intersection, the choice of the preferred path to the destination, and rerouting. (1) Turning Decisions at an Intersection: In the real world, a driver normally has to decide which way to move at an intersection, choosing to either go straight, turn left, or turn right, according to different requirements, such as avoiding road congestion; (2) Fastest Path vs. Shortest Path: A driver may choose a path based on different criteria, such as travel time, distance, personal habit, and so on. Still, most people choose paths which have the shortest distance to their destinations. However, if everybody chooses the "same" shortest path, it might actually lead to more congestion on the road, and, as a result, a longer travel time. Consequently, the fastest path to destination might not necessarily be the shortest one, since a faster path might include road segments which are longer but less congested; (3) Rerouting Reaction when Encountering an Accident or Traffic Jam: Traffic jams or car accidents could create incentives for drivers to change their routes in order to reduce travel time. However, the reaction to re-route could potentially affect the network topology. To be more specific, car accidents tend to create road congestion, which results in a higher network density. Note that, although re-routing when encountering a traffic jam is a common practice for drivers in the real world, its effects have been rarely discussed in the literature [31]. Routing protocols that predict the next hop based only on history or the use of navigation system might perform poorly when such a driving behavior is considered.

4.2 Destination Selection

As described previously, drivers tend to exhibit a bias in their destination selection [10], and thus some locations could potentially be visited more often than others. Different destination selection patterns will result in different network topologies and levels of connectivity. To simplify the discussion, let us assume that the selection of destinations follows a certain probability distribution. Here we consider three different probability distributions: pareto, exponential, and uniform.

When the selection of destinations follows a uniform distribution, it suggests that the probability of a car visiting any location on the map is uniformly distributed. On the other hand, when the selection of destination follows a pareto distribution, it implies that some locations are visited much more often than others. To understand the effects of destination selection, we setup a simulation using a 4×4 grid map with 100 cars. The length of the road segment is 400m. As shown in Fig. 1, when cars pick their destination following a pareto destination, the network will have a larger cluster coefficient [27] over time and every car will have more neighboring nodes, as compared to the cases when cars choose their destinations following an exponential or uniform distribution.

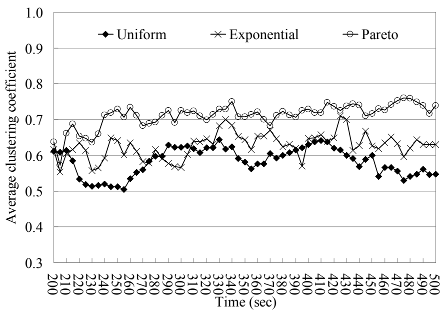


Fig. 1. Comparison of the average cluster coefficient for the three node distributions.

However, this is not unexpected, as when more cars select the same destination (*e.g.*, when students select their school as the destination), the chance that some road segments in their selected paths to the destination overlap will become higher. More overlapping road segments suggest a higher node density, shorter inter-car distance and a lower moving speed, which typically leads to a better network connectivity.

5. CASE STUDY FOR DESTINATION SELECTION

In this section, we use two case studies to demonstrate the effect of preferred routes, in particular, the selection of destinations, on the performance of practical ITS applications. We show that a destination selection model could have different effects on different ITS applications. Here we consider two types of ITS applications: V-to-I communication and data dissemination in a vehicular network. In the paradigm of V-to-I communication, a car typically needs to find a multi-hop route to the RSU to send its data. Therefore, network connectivity is a key parameter that decides the application performance. On the other hand, for data dissemination applications, the aim is to quickly disseminate data (*e.g.*, accident information) over the whole network. Therefore, the performance of such applications might depend on the concentration of the nodes in a certain area. In other words, the distribution of cluster sizes could play an important role for the effectiveness of such applications. In this section, we first briefly discuss how different destination selection models affect network connectivity and cluster size. We then use simulations to demonstrate how the destination selection could potentially affect the performance of practical ITS applications. In this section, we consider two scenarios. In the first scenario, we assume that, for traffic monitoring purposes, vehicles can collect road information using their sensors (*e.g.*, GPS), and then periodically send the sensor data to the RSUs within their radio range [32]. In the second scenario, we consider the case when a vehicle wants to disseminate information about a certain event (such as a car accident) over the whole network via vehicle-to-vehicle communication [33].

Table 1. Definition of model symbols.

symbol	Description
N	The number of cars in the network
$s_{(x,y)}$	The coordinate of the source s, s_x and s_y mean the values at the x axis and y axis respectively.
$d_{(x,y)}$	The coordinate of the destination d, d_x and d_y mean the values at the x axis and y axis respectively.
$j_{(x,y)}$	The coordinate of the intersection j, j_x and j_y mean the values at the x axis and y axis respectively.
$X_{(s,d)}$	The distance between s and d at the x axis
$Y_{(s,d)\backslash}$	The distance between s and d at the y axis
L	The length of a road segment
K	Number of intersections on the map
ς_d	The probability of choosing a destination d
R	The radio transmission range
μ	The number of cars at a road segment
$\vartheta(j)$	The number of cars encountering at intersection j

Here we define the 'network connectivity' as *The number of roads there are connected/the total number of road segments*. And we define 'connected road' as the following. We first define the 'road connectivity' $\nu = 1$ if the distance between any two adjacent cars on the road segment is less than the radio range R, and $\nu = 0$ if otherwise. When $\nu = 1$, it suggests that any car on this road segment can connect to all the other cars through multi-hop communication. Furthermore, we assume that the gap ρ between any two adjacent cars on a road segment follows an exponentially distribution. For the sake of discussion, here we do not consider the length of the car. In other words, $\sum_{i=1}^{\lceil \mu \rceil -1} \rho_i = L$, where L is the length of road segment and μ is the total number of cars on this road segment including the cars at the intersections. Therefore, the connectivity of this road segment is 1 if $\rho_{max} <= R$ where ρ_{max} is the maximum value of ρ_i, $\forall i \in \{1, 2, \ldots, \lceil \mu \rceil - 1\}$. Next, we can compute the total number of cars on a road segment $\mu_{\overline{jw}}$ for a road segment $\overline{jw}$ that lies between two intersections j and w, as the following. Let's say the number of roads connected to j and w are m and n respectively. For simplicity, here we assume that a car has the same probability to turn into any direction (*i.e.*, adjacent roads) when it is at an intersection j. Assuming there are $\vartheta(j)$ and $\vartheta(w)$ are the number of cars that arrive at the intersection j and w at time τ, respectively, then $\mu_{\overline{jw}} = \vartheta(j)/m + \vartheta(w)/n$. Therefore, we can obtain the network connectivity if we can derive the number of cars that will cluster at an intersection j.

As an example, assuming we have a grid topology and drivers choose their destinations according to a probability ς_d, such as pareto, uniform, or exponential distribution, and thus we can deduce that the number of cars targeting to destination d as $N * \varsigma_d$, where N is total number of cars in the network. We can represent the intersection on the grid map by an index j, $\forall j \in \{1, 2, \ldots, K\}$, where K is the total number of intersections on the grid map. We further assume that, if there are in total $N * \varsigma_d$ cars aiming to destination d in this network, then averagely there are $N * \varsigma_d/K - 1$ cars aiming to destination d at each intersection (except from destination d).

For evaluating the connectivity of the network, we will first derive the number of cars gathering at each intersection j. In a grid network, when the car goes from the source $s_{(x,y)}$ to the destination $d_{(x,y)}$ through intermediate intersection $j_{(x,y)}$, the car will first go from the source to the intersection j through $|j_x - s_x| = X_{(s,j)}$ unit(s) in the x direction and $|j_y - s_y| = Y_{(s,j)}$ unit(s) in the y direction, and then go from intersection j to the destination through $|d_x - j_x| = X_{(j,d)}$ unit(s) in the x direction and $|d_y - j_y| = Y_{(j,d)}$ unit(s) in the y direction. Thus, we can deduce that the possible number of paths that the car goes from s to j and then j to d are $(X_{(s,j)} + Y_{(s,j)})!/X_{(s,j)}!Y_{(s,j)}!$ and $(X_{(j,d)} + Y_{(j,d)})!/X_{(j,d)}!Y_{(j,d)}!$, respectively. And the total number of possible paths for a car to go from s to d is $(X_{(s,d)} + Y_{(s,d)})!/X_{(s,d)}!Y_{(s,d)}!$. Accordingly, the probability for a car to go from s to d through the intersection j is

$$P_{s\_j\_d} = \frac{(X_{(s,j)} + Y_{(s,j)})!}{X_{(s,j)}!Y_{(s,j)}!} \times \frac{(X_{(j,d)} + Y_{(j,d)})!}{X_{(j,d)}!Y_{(j,d)}!} \Bigg/ \frac{(X_{(s,d)} + Y_{(s,d)})!}{X_{(s,d)}!Y_{(s,d)}!},$$
$$s \neq j \neq d, \forall j_{(x,y)} = \{j_x : s_x(d_x) \leq j_x \leq d_x(s_x), j_y : s_y(d_y) \leq j_y \leq d_y(s_y)\}. \tag{1}$$

Therefore, we can deduce that the number of cars passing through the intersection j, *i.e.*,

$$P_\sigma = \sum_{d=1}^{K} \sum_{s=1}^{K} \frac{N * \varsigma_d}{K-1} \times P_{s\_j\_d}. \tag{2}$$

However, these cars might not encounter at the intersection j at the same time. So let's assume that each car has the same speed and each road segment has the same length, and each car travel across a segment by a unit time. Suppose that a car takes τ time units to arrive at the intersection j (assuming x units are used to travel in the X-direction and y units are used to travel in the Y-direction, *i.e.*, $x + y = \tau$), based on Pascal's Triangle Theory [34], the number of possible paths that this car can use to arrive at the intersection j at exactly time τ will be 2^τ. Thus, we can get the ratio of cars, *i.e.*,

$$P_\tau = \sum_{d=1}^{K}\sum_{s=1}^{K}\frac{2^\tau}{\frac{(X_{(s,j)}+Y_{(s,j)})!}{X_{(s,j)}!Y_{(s,j)}!}}, X_{(s,j)} \geq \tau, Y_{(s,j)} \geq \tau \tag{3}$$

that will encounter at the j intersection at the same time after the τ time units and then proceed to the destination d. Finally, the number of cars that will encounter at the intersection j after τ time units is

$$\vartheta(j) = P_\sigma * P_\tau = \sum_{d=1}^{K}\sum_{s=1}^{K}\frac{N * \varsigma_d}{K-1}\times 2^\tau \times \frac{(X_{(j,d)}+Y_{(j,d)})!}{X_{(j,d)}!Y_{(j,d)}!}\times\frac{X_{(s,d)}!Y_{(s,d)}!}{(X_{(s,d)}+Y_{(s,d)})!}. \tag{4}$$

Now we have the number of cars at each intersection at time τ. Next, we will compute the number of cars travelling on one particular road segment. Again, let's assume that, in a grid network, cars at the intersection j will proceed to their destinations along four different directions with equal probabilities. Accordingly, the number of cars in the segments between the intersections j and neighbor intersections $\{w1, w2, w3, w4\}$ can be obtained respectively, *i.e.*, $\mu_{\overline{j\omega_1}} = [\vartheta(j) + \vartheta(w_1)]/4$, $\mu_{\overline{j\omega_2}} = [\vartheta(j) + \vartheta(w_2)]/4$, $\mu_{\overline{j\omega_3}} = [\vartheta(j) + \vartheta(w_3)]/4$, $\mu_{\overline{j\omega_4}} = [\vartheta(j) + \vartheta(w_4)]/4$. After obtaining the number of cars on a road segment, we can then compute the connectivity of this road segment, as discussed previously.

Based on the above model, we perform a simple simulation experiment using a 5×5 grid map. We first vary the number of cars in the simulations. The road length is set to 400m and the radio transmission range is 250m. The selection of destination is based on the pareto, uniform and exponential distribution, respectively. As shown in Fig. 2, the network connectivity is generally better when drivers select their destinations following a uniform distribution. We also vary the radio transmission rage. As shown in Fig. 3, as we increase the range of radio transmission, the effect of destination selection becomes less obvious.

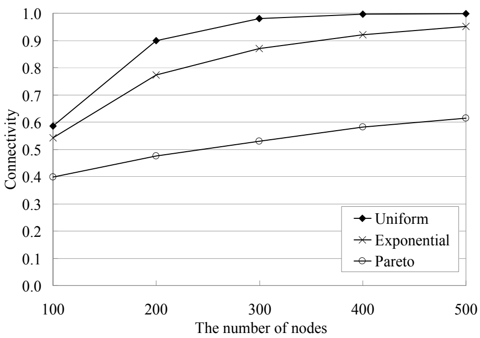


Fig. 2. Network connectivity as a function of node number for different destination selection models.

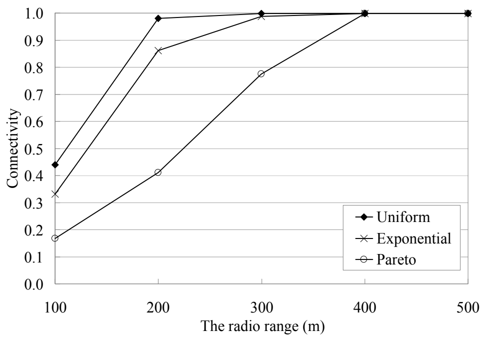


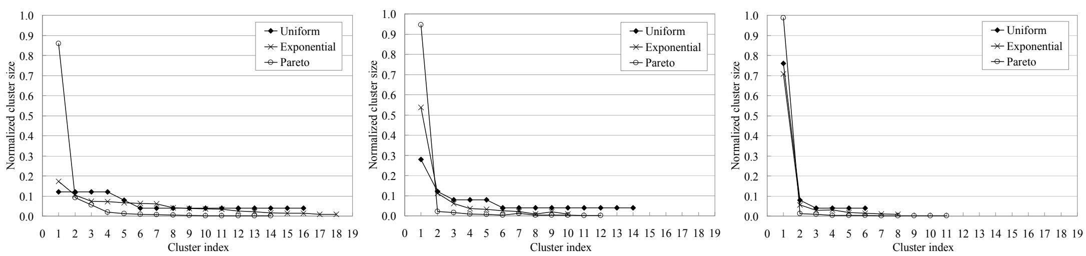
Fig. 3. Network connectivity as a function of radio range for different destination selection models.

Next, we consider the effect of preferred destination selection on the distribution of network cluster sizes. We define a cluster as a group of cars that can find at least one multipath route to each other and the cluster size as the number of the cars in the same cluster, thus cars travelling on two adjacent 'connected roads' will be in the same cluster. If we model the road network as a graph in which that roads are the edges and intersections are the vertexes in the graph, we can then use a greedy algorithm as the following to search for all the adjacent connected roads to computer clusters and their sizes. T_i in the following algorithm represents a cluster i.

Input: a connected graph $G = (V,\ E),\ T \leftarrow \Phi,\ V_q \leftarrow \Phi$
Output: $T = \{T1,\ T2,\ \ldots, Tn\}$, a set of n spanning trees in G, $T_i = (V_{T_i}, E_{T_i}), i \in \{1, 2, \ldots, n\}$
Initially, $i \leftarrow 1,\ V_{tmp} \leftarrow V$
While ($V_{tmp} \notin \Phi$) do
  $V_{T_i} \leftarrow \{v_0\}$, v_0 is arbitrarily chosen from $V \setminus V_q$ as the root of the tree, $E_{T_i} \leftarrow \Phi$
    for $k \leftarrow 1$ to $|V| - |V_q|$-1, do
      if (finding an segment $e^* = (u^*, v^*)$ with connectivity is 1 among all the edges $e = (u,\ v)$ such that $u \in V_{T_i}$ and $v \in V \setminus (V_q \bigcup V_{T_i})$)
      {
        $V_{T_i} \leftarrow V_{T_i} \cup \{v^*\}$
        $E_{T_i} \leftarrow E_{T_i} \cup \{(u^*, v^*)\}$
      }
    end for
    $V_q \leftarrow V_q \cup V_{T_i}$

    $V_{tmpq} \leftarrow V\ \text{-}\ V_q$
    $i{+}{+};$
end while
$n \leftarrow i$
for $i\ \leftarrow 1$ to n do
  $N(T_i) = \sum_{k=1}^{|V_{T_i}|} \vartheta(v_k), \forall v_k \in V_{T_i}$
end for

Accordingly, we can get the size of each cluster (*i.e.*, the summation of the number of cars in the connected tree), $N(T_i)\ \forall i \in \{1, 2, \ldots, n\}$. We run the simulation again using the same grid topology as discussed previously, and orderly plot the normalized cluster size for different destination selection models. As shown in Fig. 4, the axis represents the



(a) The number of nodes is 25. (b) The number of nodes is 50. (c) The number of nodes is 100.

Fig. 4. The statistic of clusters for different node densities when different destination selection models are used.

index of the cluster sorted by the cluster size and y-axis is the normalized cluster size (*i.e.*, cluster size/total number of cars). Our results show that, when the pareto distribution is used to model the destination selection process, most of the cars will concentrate in the same cluster. Hence, we can expect that a data dissemination application will have smaller forwarding delays when the drivers choose their destinations following a pareto distribution, as compared to when uniform or exponential distribution is used. In addition, we observe that, when the pareto distribution is employed, the cluster size distribution is less affected by the node density.

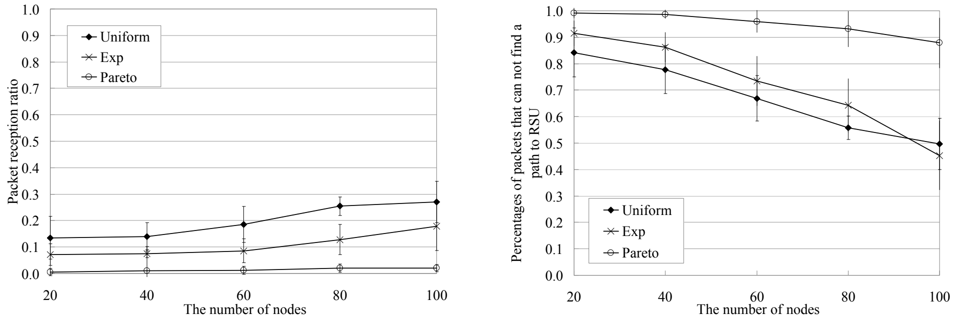
From the above discussion, we can see, even with the same destination selection model, it could have different effects on different type of ITS applications. Next, we further demonstrate the importance of destination modeling for two practical ITS scenarios.

5.1 Application A: Traffic Monitoring

For the traffic monitoring scenario, we use a 4×4 grid map. The length of each grid is 400m. We place a RSU at the center of the map. Each car periodically (*i.e.*, every 5 seconds) broadcasts the sensor information it has collected. Nodes overhearing the sensor data will rebroadcast the packet (*i.e.*, via flooding). We employ simple MAC in ns-2 as the underlying MAC protocol. Simple MAC supports CSMA (without the backoff mechanism when data needs to be retransmitted). In this scenario, we consider the packet reception ratio at RSUs when different destination selection models are used (*i.e.*, with the uniform, exponential, and pareto distributions). The packet reception ratio is defined by *The number of packets received by any RSU / The number of packets sent by the cars.* In our simulations, many cars' destinations fall in the bottom part of the map when pareto and exponential distributions are used. Note that a packet will be discarded immediately if it cannot be forwarded to RSU through flooding. We do not considered a store-and-forward mechanism used by the car to temporarily store the packets in this scenario.

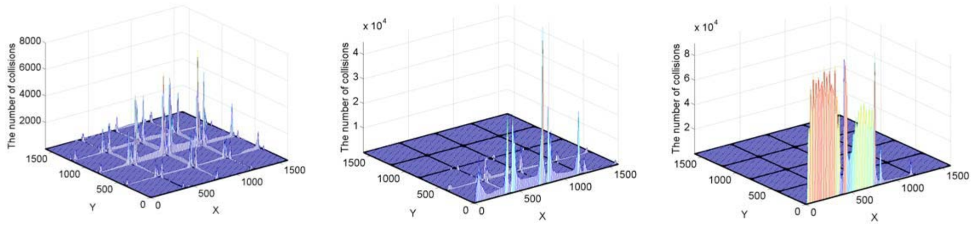
As shown in Fig. 5 (a), when cars select their destinations following a uniform distribution, the application performance is better than when the other two distributions are employed. The reason is that lots of the cars tend to use routes in the bottom half of the map when selecting their destinations following an exponential or pareto distribution. In fact, when pareto distribution is used, many cars choose the same route to their destinations. Therefore, some roads become very congested, while others have only a few cars. In other words, cars tend to cluster in a certain area when their destination selection follows a pareto distribution. If the center of the cluster is far away from a RSU, it is very likely that cars cannot find a path (either single-hop or multi-hop) to send their data to the RSU at the time when the sensor data is broadcast. As shown in Fig. 5 (b), there are more packets that cannot find a path to a RSU when the destination selection follows a pareto distribution as compared to when the other two distributions are used. As shown in Fig. 6, when cars select their destinations following a uniform distribution, most of the MAC-layer collisions occur at the intersections and the central part of the map. In contrast, when cars select destinations following an exponential or pareto distribution, more than 90% of collisions happen in the bottom part of the map.

On the other hand, if the center of the cluster is close to a RSU, the application can be greatly improved when cars select their destinations following a pareto or exponential distribution. For example, as the results show in Fig. 7 if we change the location of the



(a) Packet reception ratio. (b) Ratio of packets that cannot find a path to RSU.

Fig. 5. Effects of destination selection on traffic monitoring application.



(a) Uniform distribution. (b) Exponential distribution. (c) Pareto distribution.

Fig. 6. Distributions of MAC-layer collisions when different destination selection models are used.

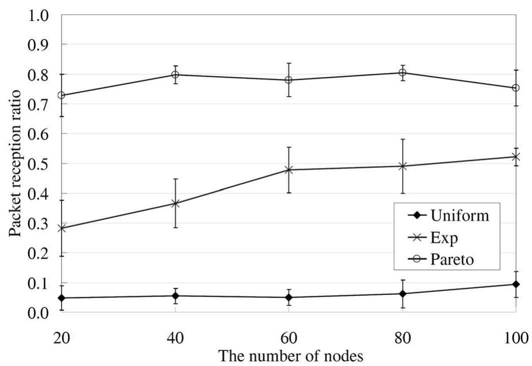
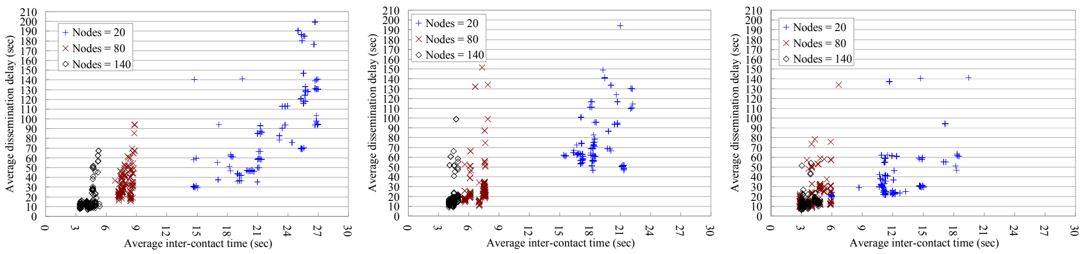


Fig. 7. The combined effects of driver destination selection and the location of RSU.

RSU from the center of the map to the bottom left corner, the packet reception ratio for the exponential and pareto distributions are significantly improved, as compared to the results in Fig. 5 (a). Note that the application performance when the destination selection follows a uniform distribution is reduced since half of the cars traveling to the upper part of the map are not able to find a path to the RSU. Similarly, if cars select their destinations following a uniform distribution while RSUs are located on a remote part of the map (*e.g.*, the corner), the preferred destination has only little effect on the performance of the application. The above insight suggests that how to select connection pairs in simulations could be very important, since the results might be totally different when different mobility models are employed. Most of the vehicular network simulations in the literature tend to select their node destinations uniformly, which will favor the scenario when RSUs are located near the center of the map. In addition, from the perspective of network efficiency, our observation provides an incentive to consider users' preferred routes and destinations when one wants to deploy some RSUs for ITS applications in the real world, as previously observed by Ding and Xiao [9].

5.2 Application B: Event Broadcasting

Next, we look at the effect of destination selection on disseminating data in a vehicular network. We consider a scenario in which a car wants to broadcast an event (*e.g.*, a car accident) over the whole network via vehicle-to-vehicle communication in a flooding-like fashion (*e.g.*, using epidemic routing). Unlike the previous scenario, here we consider that the store-and-forward mechanism is employed so that a car can carry a packet around when it cannot immediately find the next forwarder. The performance metric we are interested in here is how long the message takes to reach every car in the network. The road topology is the same as that for application A, and the sender is randomly selected. For simplicity, here we only consider three different node densities: 20, 80 and 140. Generally speaking, the delay in data dissemination is a function of the inter-contact time of vehicles. Here we define data dissemination delay as the duration from when the originating car sends out the event until when the other cars receives the event, and inter-contact time as the time interval between two contacts (*i.e.*, the duration from when one car encounter finishes and the next one begins).



(a) Uniform distribution. (b) Exponential distribution. (c) Pareto distribution.

Fig. 8. Effect of different destination selection models on data dissemination delay.

As shown in Fig. 8 (each point in the graph is the result from one simulation), we find that the average inter-contact time and dissemination delay are larger when cars choose their destinations following a uniform distribution, as compared to when they follow an exponential or pareto distribution. This is because many cars might cluster together as their selected destinations and the paths to them are similar when they choose destinations following either of these distributions. As a result, the inter-contact distance between cars will be shorter and, consequently, the inter-contact time and dissemination delay are smaller. In addition, we observe that the dissemination delay is not significantly affected by the changing node density when the node density is high (*e.g.*, when nodes = 80 and 140), if the selected destinations follow a pareto distribution (*i.e.*, most of the cars are in the same cluster). Note that some large delays in Fig. 8 (*e.g.*, > 130 seconds) are because we happened to select a sender that was far from all the other nodes in that simulation.

Replication strategy is an important parameter when designing a vehicular network protocol. Multiple-copy forwarding is commonly used to cope with intermittent network connectivity in a vehicular network. For example, epidemic routing floods the network to exploit the best possible delivery delay brought by mobility. This scheme achieves optimal delay assuming unlimited bandwidth and relay buffers. In general, a multiple-copy scheme that allows multiple replicates of the same message to be distributed on multiple relay nodes can improve delivery delay by providing more diverse delivery paths. However, it also incurs significant overhead on the storage space and communication bandwidth requirements of the relay nodes. When multiple messages have to be delivered simultaneously across a vehicular network, these common network resources are under contention. In this work, we show that the distribution of node density can be a function of the destination selection model. For example, as previously in our simple grid network example, more nodes concentrate at the center of map when the uniform distribution is employed, but cluster in the bottom part of the map when the pareto distribution is used. One might be able to utilize such insights to design a protocol that can dynamically adjust the replication policy that adapts to the node distribution, assuming that the distribution of drivers' preferred destinations can be known in advance.

6. CONCLUSIONS AND FUTURE WORK

Performing a realistic VANET simulation is challenging, since many factors could affect the node mobility in real life situations. In this paper, we discuss the effect of preferred route and destination on the network topology and application performance.

We show that a destination selection model can have different effects for different ITS applications. Furthermore, we observe that simulation results are not significantly affected by different node density settings when cars pick their destination following a pareto distribution.

To sum up, selecting an appropriate level of details in the mobility model for a VANET simulation is important. As for our future work, we plan to look at how other driving behaviors, such as lane changing, car following and intersection behavior, affect the results of vehicular simulations. In addition, we plan to use real-world vehicle traces to derive a trace-based destination selection model.

REFERENCES

1. L. Breslau, D. Estrin, K. Fall, S. Floyd, J. Heidemann, A. Helmy, P. Huang, S. McCanne, K. Varadhan, Y. Xu, and H. Yu, “Advances in network simulation,” *IEEE Computer*, Vol. 33, 2000, pp. 59-69.
2. X. Chang, “Network simulations with OPNET,” in *Proceedings of the 31st Conference on Winter Simulation*, Vol. 1, 1999, pp. 307-314.

3. QualNet network simulator, http://www.scalable-networks.com/.
4. G. D. B. Cameron and G. I. D. Duncan, "Paramics: parallel microscopic simulation of road traffic," *Journal of Supercomputing*, Vol. 10, 1996, pp. 25-53.
5. A. Halati, H. Lieu, and S. Walker, "Corsim-corridor traffic simulation model," in *Proceedings the Traffic Congestion and Traffic Safety in the 21st Century Conference*, 1997, pp. 570-576.
6. M. Fellendorf, "VISSIM: A microscopic simulation tool to evaluate actuated signal control including bus priority," in *Proceedings of the 64th Institute of Transportation Engineers Annual Meeting*, 1994, pp. 1-9.
7. A. K. Saha and D. B. Johnson, "Modeling mobility for vehicular ad hoc networks," in *Proceedings of the 1st ACM International Workshop on Vehicular Ad Hoc Networks*, 2004, pp. 91-92.
8. F. Dressler and C. Sommer, "On the impact of human driver behavior on intelligent transportation systems," in *Proceedings of the 71st IEEE Vehicular Technology Conference*, 2010, pp. 1-5.
9. Y. Ding and L. Xiao, "SADV: static-node-assisted adaptive data dissemination in vehicular networks," *IEEE Transactions on Vehicular Technology*, Vol. 59, 2010, pp. 2245-2455.
10. M. A. Abdelaty, K. M. Vaughn, R. Kitamura, P. P. Jovanis, and F. L. Mannering, "Models of commuters' information use and route choice: Initial results based on southern California commuter route choice survey," *Transportation Research Record*, 1994, pp. 46-55.
11. A. M. Tawfik, H. A. Rakha, and S. D. Miller, "An experimental exploration of route choice: Identifying drivers choices and choice patterns, and capturing network evolution," in *Proceedings of the 13th International IEEE Conference on Intelligent Transportation Systems*, 2010, pp. 1005-1012.
12. D. Zhao and C. Shao, "Empirical study of drivers learning behavior and reliance on VMS," in *Proceedings of the 13th International IEEE Conference on Intelligent Transportation Systems*, 2010, pp. 1614-1619.
13. H. Li, R. Guensler, and J. Ogle, "An analysis of morning commute route choice patterns using gps based vehicle activity data," in *Proceedings of the 84th Annual Meeting of the Transportation Research Board*, 2005, pp. 162-170.
14. X. Zhang, J. Kurose, B. Levine, D. Towsley, and H. Zhang, "Study of a bus-based disruption-tolerant network: Mobility modeling and impact of routing," in *Proceedings of the 13th Annual ACM International Conference on Mobile Computing and Networking*, 2007, pp. 195-206.
15. B. David and A. David, "Dynamic source routing in ad hoc wireless networks," in *Mobile Computing*, Vol. 35, Kluwer Academic, 1996, pp. 153-181.
16. J. Yoon, M. Liu, and B. Noble, "Random waypoint considered harmful," in *Proceedings of the 22nd Annual Joint Conference of the IEEE Computer and Communications Societies*, 2003, Vol. 2, pp. 1312-1321.
17. M. Treiber, A. Hennecke, and D. Helbing, "Congested traffic states in empirical observations and microscopic simulations," *IPhys. Rev.*, Vol. 62, 2000, pp. 1805-1824.
18. F. Bai, N. Sadagopan, and A. Helmy, "Important: a framework to systematically analyze the impact of mobility on performance of routing protocols for ad hoc networks," in *Proceedings of the 22nd Annual Joint Conference of the IEEE Computer*

and Communications Societies, 2003, pp. 825-835.

19. H. Huang, Y. Zhu, X. Li, M. Li, and M. Y. Wu, "Meta: A mobility model of metropolitan taxis extracted from gps traces" in *Proceedings of IEEE Wireless Communications and Networking Conference*, 2010, pp. 1-6.
20. H. Dia and S. Panwai, "Modelling drivers' compliance and route choice behavior in response to travel information," *Nonlinear Dynamics*, Vol. 49, 2007, pp. 493-509.
21. T.-L. Liu and H.-J. Huang, "Multi-agent simulation on day-to-day route choice behavior," in *Proceedings of the 3rd International Conference on Natural Computation*, Vol. 5, 2007, pp. 492-498.
22. Z. Shenpei and Y. Xinping, "Drivers route choice model based on traffic signal control," in *Proceedings of the 3rd IEEE Conference on Industrial Electronics and Applications*, 2008, pp. 2331-2334.
23. J. Zhao and Q. Li, "A method for modeling drivers' behavior rules in agent-based traffic simulation," in *Proceedings of the 18th International Conference on Geoinformatics*, 2010, pp. 1-4.
24. D. Guo, X. Li, M. Liu, and L. Zhang, "Model of traffic path choice based on game theory and induction mechanism," in *Proceedings of the 9th International Symposium on Distributed Computing and Applications to Business Engineering and Science*, 2010, pp. 495-498.
25. T. Dingus, M. Hulse, S. Jahns, J. Alves-Foss, S. Confer, A. Rice, I. Roberts, R. Hanowski, and D. Sorenson, "Development of human factors guidelines for advanced traveler information systems and commercial vehicle operations: Literature review," FHWA-RD-95-153, Federal Highway Administration, 1996.
26. O. Jan, A. J. Horowitz, and Z.-R. Peng, "Using global positioning system data to understand variations in path choice," *Transportation Research Record*, No. 1725, 2000, pp. 37-44.
27. M. Fiore and J. Härri, "The networking shape of vehicular mobility," in *Proceedings of ACM MobiHoc*, 2008, pp. 261-272.
28. MOVE, http://lens.csie.ncku.edu.tw/MOVE/.
29. D. Krajzewicz, G. Hertkorn, C. Rőssel, and P. Wanger, "Sumo (simulation of urban mobility); an open-source traffic simulation," in *Proceedings of the 4th Middle East Symposium on Simulation and Modelling*, 2002, pp. 183-187.
30. S. J. Leon, *Linear Algebra with Applications*, Pearson, NJ, 2006.
31. P. Lai, X. Wang, N. Lu, and F. Liu, "A reliable broadcast routing scheme based on mobility prediction for VANET," in *Proceedings of IEEE Intelligent Vehicles Symposium*, 2009, pp. 1083-1087.
32. L. Wischhof, A. Ebner, and H. Rohling, "Information dissemination in self-organizing intervehicle networks," *IEEE Transactions on Intelligent Transportation Systems*, Vol. 6, 2005, pp. 90-101.
33. T. Nadeem, S. Dashtinezhad, C. Liao, and L. Iftode, "TrafficView: traffic data dissemination using car-to-car communication," *ACM SIGMOBILE Mobile Computing and Communications Review*, Vol. 8, 2004, pp. 6-19.
34. J. H. Conway and R. K. Guy, "Pascal's triangle," in *The Book of Numbers*, Springer-Verlag, NY, 1996, pp. 68-70.

Kun-Chan Lan (藍崑展) received his Ph.D. degree from Computer Science at University of Southern California in 2004, advised by Professor John Heidemann. From 2004 to 2007, he joined the Network and Pervasive Computing Program at NICTA (National ICT Australia) in Sydney as a researcher. He is currently an Assistant Professor at the Department of Computer Science and Information Engineering of National Cheng Kung University.

Chien-Ming Chou (周建銘) received his B.S. degree from Computer Science at Vanung University of technology in 2005 and M.S. degree from Information and Communication Engineering at Chaoyang University of Technology in 2007. He is currently working for his Ph.D. degree in Department of Computer Science and Information Engineering, National Cheng Kung University. His research interests include network simulation, network measurement, opportunistic routing, WiMAX and DSRC protocol, and mobility model.

Ching-Fang Yang (楊清芳) received the B.S. and M.S. degrees in Electrical Engineering from National Cheng Kung University, Taiwan, in 1999 and 2002, respectively. From 2003 to 2008, he has been with the Industrial Technology Research Institute as a Research Engineer. He obtained his Ph.D. degree in the Department of Electrical Engineering at National Cheng Kung University in 2010. Currently, he is a Postdoctoral Fellow in National Cheng Kung University. His current research interests are in the areas of optical networks, and vehicular network management.