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Available online: 11 Aug 2011

To cite this article: Ivan Wang-Hei Ho, Robin J. North, John W. Polak & Kin K. Leung (2011): Effect of Transport Models on Connectivity of Interbus Communication Networks, Journal of Intelligent Transportation Systems, 15:3, 161-178

To link to this article: \url{http://dx.doi.org/10.1080/15472450.2011.594691}

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Effect of Transport Models on Connectivity of Interbus Communication Networks

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Vehicular Ad-Hoc Networks (VANETs) attract considerable research and commercial interest with promising applications in a number of areas including cooperative vehicle-highways systems, sensor networks, and safety systems. However, as a result of high speed and variable driver behavior, automotive ad-hoc networks behave in fundamentally different ways to the most prevalent models in Mobile Ad-Hoc Network (MANET) research. Previous work in MANETs has mostly assumed that the mobile nodes move randomly with an unconstrained mobility model, and it is clear that a random mobility model is not adequate to represent the major characteristics of real-world vehicle motions and may therefore lead to unreliable results. Recent studies of VANETs have attempted to introduce macro- and micromobility constraints to model vehicle motions, but they have mostly focused on modeling the mobility of generic private vehicles. Given the potential for the coordinated deployment of network nodes on centrally managed fleet vehicles, it has become important to model the characteristics of a VANET featuring vehicles of different types, with systematically different behavior patterns. In this article, the authors study the connectivity of mobile ad-hoc networks that consist of buses moving in urban area and examine the implications for transport-related services. Buses have a unique set of behavior characteristics (e.g., fixed routes, schedules, bus stops, specific priorities), which gives rise to distinct effect on node connectivity in the communication network. Through extensive simulations on the basis of real bus routes in central London, the authors (a) demonstrated the effect of the locations of stops and the prevailing traffic patterns on node connectivity (including the distributions of contact duration and intercontact time between buses) and (b) explored its implication on the design of a dissemination system to capture and disseminate data. Their results give a key message that the mobility of buses has to be modeled explicitly, and such kind of knowledge of connectivity among buses will be significant for the studies of routing algorithms and other networking functions in interbus communication networks.

Keywords Connectivity; Interbus Communication Networks; Transport Models; Vehicular Ad-Hoc Networks

INTRODUCTION

Vehicular Ad-Hoc Networks (VANETs), a subclass of Mobile Ad-Hoc Networks (MANETs), consist of vehicles moving on urban streets, communicating with each other wirelessly in the absence of any other communications infrastructure. Because of their readily deployable nature and potential functions in road safety, detecting traffic accidents and incidents, and reducing traffic congestion, VANETs attract significant attention from the research community. There are a number of previous demonstrations of using existing wireless technology for achieving vehicle-to-vehicle communications in the real world. For example, Festag, Fubler, Hartenstein,
Sarma, and Schmitz (2004) described the real-world field trials of a car-to-car communication platform with an IEEE 802.11 air interface, whereas Bucciol, Masala, Kawaguchi, Takeda, and De Martin (2005) conducted video-streaming experiments between two vehicles moving on highway and urban road networks. These experiments show that existing technology is feasible for building connections between mobile users in cars with intermittent connectivity. VANETs also have applications in the design and operation of sensor networks. An example of an application of this sort is the MESSAGE project, which aims to deploy a mobile wireless air quality sensor network on buses in London (Cohen, Darlington, North, and Polak, 2007).

However, the constraints associated with vehicle movements, varying driver behavior, and high speed cause rapid topology changes, frequent fragmentation of the network, and limited utility from network redundancy. These features cause the characteristics of VANETs to differ substantially from traditional, random-motion MANET models. These differences also have implications for the VANET architecture, ranging from the physical to application layers in the Open System Interconnection model for communications and for computer network protocol design.

In general, the effect of mobility on the performance of communication protocols can be described using the block diagram shown in Figure 1. First, different mobility models have different degrees of spatial dependence, temporal dependence, relative speeds and geographic restrictions, which give rise to different (communication) link durations and intercontact time between nodes, and thus distinct (communication) path availabilities for multihop transmissions. Network connectivity, in turn, influences the performance of the communication protocol. It has been shown that a longer link duration will result in higher throughput (Bai, Sadagopan, and Helmy, 2003). Therefore, to ensure the design feasibility of VANETs, we require a fundamental understanding of the relations between vehicular mobility and node connectivity (the first two blocks in Figure 1), which is the focus of this article.

There are a number of studies on node connectivity in MANETs. These include theoretical studies that explore the critical radio transmission range for achieving full connectivity (Bettstetter, 2004; Gupta and Kumar, 1998; Santi, Blough, and Vainstein, 2001; Wang, Liu, Goeckel, Towsley, and Westphal, 2008). There are also recent works that aim to model connectivity of vehicles on a one-dimensional highway through modeling the space headway (Ukkusuri and Du, 2008) and using synthetic mobility model (Khabazian and Mehmet Ali, 2008). Bai and colleagues (Bai et al., 2003; Bai, Sadagopan, Krishnamachari, and Helmy, 2004) have investigated the distribution of connectivity parameters with various random mobility models. Furthermore, the distribution of intercontact time between generic mobile nodes was explored on the basis of random mobility models (Cai and Eun, 2007) and empirical human mobility traces (Chaintreau et al., 2006; Karagiannis, Le Boudec, and Vojnovic, 2007).

However, most of these previous studies have neglected real-world constraints when modeling node mobility. For example, most of the analytical studies assume that nodes are distributed homogeneously throughout the network. In addition, the popular random waypoint model is widely used in MANET research for ease of analysis, but it assumes that mobile nodes move in an open-field without any obstacles and ignores real-world factors affecting vehicles such as street layouts and intervehicular interactions. It is clear that this kind of random mobility model cannot adequately capture the major characteristics of vehicular traffic (the reader can refer to our previous work (Ho, Leung, Polak, and Mangharam, 2007) for the comparison of node connectivity of unconstrained random waypoint and road-constrained car-following models), and so there is a necessity to introduce realistic mobility models for VANETs, which is critical for reliable evaluation of the communication system performance.

In transport studies, when dealing with vehicular traffic, researchers usually refer to the macro- and micromobility descriptions (Harri, Filali, and Boonet, 2007) for modeling the driver-to-infrastructure and driver-to-driver interactions, respectively. Macroscopic mobility (a) describes gross quantities of interest (e.g., density or average velocity of vehicles) and (b) considers vehicle movements to be analogous to fluid dynamics; microscopic mobility (a) treats each vehicle as a unique individual and (b) models its behavior with more detail but higher computational cost.

A number of studies restrict nodes’ macromobility on highway and grid topologies. For example, the Freeway and Manhattan models are described in Bai et al.’s (2003) study, and Yang and Recker (2005) evaluated through simulation the feasibility of traffic information propagation in freeway and arterial grid

![Figure 1](https://example.com/figure1.png)  
**Figure 1** Block diagram illustrating the effect of mobility on the performance of communication protocols.
networks through information exchange among vehicles. However, these road topologies are simple and regular, and many other transport features (e.g., multiple lanes, traffic lights, stop signs) are neglected.

Recent VANET research has tried to incorporate various macro- and micromobility factors into the models. For example, Saha and Johnson (2004) modeled vehicle mobility on a real street map from the Topologically Integrated Geographic Encoding and Referencing (TIGER) database (2009e); however, they neither model any interactions between vehicles nor include traffic control at road intersections. The Street Random Waypoint (STRAW) Model (Choffnes and Bustamante, 2005) introduces traffic control and stop signs at road intersections and the car-following interactions between vehicles moving in an urban grid. Mahajan, Potnis, Gopalan, and Wang (2007) proposed several simulation models that account for various urban constraints such as street layout, traffic rules, multilane roads, acceleration, and radio frequency attenuation caused by obstacles. That research extended Jardosh, Belding-Royer, Almeroth, and Suri’s (2003) work, which suggested an obstacle-based mobility model, wherein the obstacles are used to define the movement pathways of the mobile nodes and to attenuate radio transmissions.

As an alternative to purely simulation driven analyses, other studies have used real-world mobility traces for evaluating MANET performance (Krüm and Horvitz, 2005; Zhang, Kurose, Levine, Towsley, and Zhang, 2007). Although these mobility traces capture real-world vehicle activity, they are case-specific traces and therefore difficult to generalize because vehicles typically alter their trajectory on the basis of prevailing traffic conditions.

Nevertheless, when considering these studies as a whole, it appears that none considers a mix of mobile nodes attached to different types of vehicles with significantly different mobility patterns, rules, and priorities on the road. For example, generic private cars have no designated routes or fixed origins and destinations, whereas scheduled transport systems (e.g., buses) have structured mobility patterns with fixed routes and timetables, origins, and destinations. Motivated by the requirements of the Mobile Environmental Sensing System Across Grid Environments (MESSAGE) project (2009f), we aimed to study the effect of various transport factors on connectivity of an interbus communication network and explore its communication capability for disseminating pollutant and other sensor data.

Our main contributions in this article are as follows:

- We developed a simulation framework for simulating a semirealistic interbus communication network in central London and demonstrated the effect of various macroscopic and microscopic transport models on node connectivity. In addition, we studied the fundamental properties of the contact duration and intercontact time between vehicles, which have been critical metrics in MANET research in determining the capacity and routing delay of communication networks as well as in choosing various scheduling or forwarding algorithms. Such findings will provide guidelines on mobility modeling, performance analysis, and protocol design in VANETs.
- We investigated the discrepancies between the connectivity statistics of private vehicles and buses, which show the importance of modeling bus mobility independently. In particular, we found that multihop communication paths have much poorer connectivity statistics than do single-hop communication links in the bus network mobility scenario. This finding raises the issue of the feasibility of multihop transmissions for real-time applications in interbus communication networks, with implications for the types of services such a network may support.
- We identified the network requirements (e.g., data rate, data latency) for a set of transport-related data-dissemination services and quantify the feasibility of disseminating such data among buses. We explored from an e-Science and a transport perspective of the effect of the characteristics of the communication network on the rest of the system design.

A TRANSPORT MODELING FRAMEWORK FOR REALISTIC SIMULATION OF VANETS

We present in this section a framework that captures macroscopic and microscopic behavior characteristics of transport networks to facilitate more realistic study of vehicular communications networks. There are two major building blocks for modeling real-world vehicular movements: mobility constraints and vehicular traffic generation (see Figure 2). The following subsections describe these blocks and their components.

Mobility Constraints

The mobility constraints define the relative degree of freedom of vehicle movements. The vehicle is macroscopically constrained by the road network topology, per-road characteristics and obstacles (e.g., road capacity, speed limits); it is microscopically influenced by neighboring vehicles and the driver’s behavior in relation to them.

1. Road network: The motion of vehicle is restricted to the geometry of the road topology. The road network contains different categories of streets and multiple lanes, and each road segment is associated with a speed limit, which restricts the velocity of the leading vehicle and thus the following cars on the road. Moreover, traffic lights are located at road junctions. These act as gates on the road and cause bunching of vehicles while separating vehicles into clusters, or platoons. Therefore, traffic lights may be expected to have a strong effect on the node connectivity of communication network.
2. Neighboring vehicles: Unlike generic mobile nodes in MANET simulations, real vehicles cannot pass through a space already occupied by another vehicle. Instead,
neighboring vehicles influence one another, with their interdependent motion being defined by their individual driving behavior. Two classes of interactions are specifically modeled.

a. Acceleration models: Two groups of acceleration model are necessary: car-following models, which describe the acceleration drivers apply in reaction to the behavior of the vehicle in front; and general acceleration models, which apply when drivers do not closely follow their leaders. A car-following model adapts a following car's mobility according to a set of rules in order to maintain a safe distance and avoid collision with the lead vehicles. A number of alternative formulations exist, including psychophysical models, linear models, cellular automata, and fuzzy logic models (Brackstone and McDonald, 1999).

b. Lane-changing models: Modeling lane-changing behavior is a more complex task. It consists of mainly two steps: (a) the lane-selection process, that is, the decision to consider a lane change and the lane choice; and (b) the decision to execute the lane change. Lane changes are mandatory (when a driver must leave the current lane) or discretionary (when a driver chooses to improve driving condition). Gap-acceptance models are used to model the execution of lane changes. Some widely used models in transport studies include the Gipps Model (Gipps, 1986) and Wiedemann Psycho-Physical Model (Wiedemann, 1991) for lane changing.

**Vehicular Traffic Generation**

These models are responsible at a macroscopic level for generating traffic flows consisting of different types of vehicles, which has not been addressed in previous work on connectivity modeling. In our simulations, we considered two types of vehicles: buses and generic private vehicles. We used the vehicular traffic generation model to define the traffic flow and the vehicle density on the basis of overall network considerations. The model then considers the characteristics of vehicles according to their types and assigns them with different traffic patterns, rules, and priority.

Every vehicle in the network has an origin and a destination. The position may be random, random restricted on a graph, or based on a set of attraction points. After having defined the start and end points, a trip, which consists of a list of waypoints, may be generated randomly, with predefined routes, or with algorithms such as Dijkstra’s algorithm between the points. In this article, we used two different traffic generation models.

1. **Bus traffic generation:** Buses have fixed origins and destinations, as well as predefined bus routes and timetables. While en route, the bus stops at bus stops to load and unload passengers. In our simulation, we generated bus traffic on the basis of real bus route data provided by London Buses. In particular, we acquired the list of waypoints that define the bus routes and the specific positions of bus stops along the routes. In London, measures have been taken to reduce the effect of congested traffic on bus operations through the creation of bus-only lanes. Traffic lights cause bunching of vehicles, and bunching of buses is not a desirable phenomenon, especially from the perspective of bus passengers. To combat this, bus priority measures have been installed at numerous junctions in London to reduce delay and regulate the headway between buses on the same route. There are also many roads along which multiple bus routes operate and interact. All of these network characteristics combine to affect the spatial density of the buses and hence the network connectivity.

2. **Background traffic generation:** Traffic that consists of other, noncommunicating vehicles (other than buses) may cause congestion on the road that delays the bus journey. In this study, we generated background vehicle traffic with random origins and destinations on the road network, following random walk or sightseeing trip models to wander around the study region. When a background vehicle passes through a road intersection, it randomly selects a new speed within a user-defined range and chooses a direction (e.g., to turn left,
turn right, or go straight) in which to proceed. Vehicles may also stop at the intersections because of traffic signals. The vehicle randomly walks until it is a certain distance (e.g., 1 km) from the starting point and then takes the shortest path back to the starting point before it starts again along a different random path. By distributing the origins around the network, this allows a pseudorealistic distribution of background traffic to be generated.

**NODE CONNECTIVITY METRICS**

We used the node connectivity metrics that Ho et al. (2007) introduced to evaluate multihop connectivity in the simulated bus network. In this section, we restate these metrics and provide further elaboration of each parameter.

Let $X_k(i, j, t)$ be a random variable for indicating the single-hop connectivity between nodes $i$ and $j$ at time $t$ such that it equals 1 when $D_{ij}(t) \leq R$, and 0 otherwise, where $D_{ij}(t)$ denotes the Euclidean distance between nodes $i$ and $j$ at time $t$, and $R$ is the transmission range of a mobile node.

In general, we used $X_k(n_i, n_{k+1}, t)$ to indicate multihop connectivity, where $k \geq 1$ is an integer that denotes the number of hops in the communication path $p = \{n_1, n_2, ..., n_{k+1}\}$, between nodes $n_i$ and $n_{k+1}$. In particular, $X_k(n_1, n_{k+1}, t) = 1$ if and only if $X_{i}(n_1, n_{k+1}, t) = 1 \forall i \in \{1, 2, ..., k\}$; AND $X_{i}(n_1, n_{k+1}, t) = 0 \forall i \in \{1, 2, ..., k-1\}$. Otherwise, $X_k(n_1, n_{k+1}, t) = 0$. This means that nodes $n_i$ and $n_{k+1}$ are connected with at least one $k$-hop path at time $t$, given that they cannot be connected with less than $k$ hops at that time. We then defined the following:

1. **Number of connected node pairs (k-hop):** We denote this as $P_k$. It is the number of node pairs $(i, j)$ that have ever been connected with at least one $k$-hop path throughout the simulation period. In particular, $P_k$ is the number of node pairs $(i, j)$ such that $X_k(i, j) = \sum_{t=0}^{T} X_k(i, j, t) > 0$, where $T$ is the total simulation period.

2. **Number of connected periods (k-hop):** The number of connected periods of the $k$-hop path between a pair of nodes $i$ and $j$, denoted as $CP_k(i, j)$, is the number of times the path status between them changes from down to up. Mathematically,

$$CP_k(i, j) = \sum_{t=0}^{T} C_k(i, j, t)$$


3. **Path duration (k-hop):** This is the average duration in time of the $k$-hop path existing between two nodes $i$ and $j$. It is a measure of the stability of the path. Mathematically,

$$PD_k(i, j) = \frac{\sum_{t=0}^{T} X_k(i, j, t)}{C_k(i, j)}$$

We define $PD_k(i, j) = 0$ if $C_k(i, j) = 0$. Note that $PD_k(i, j)$ represents the single-hop link duration between the node pair $(i, j)$.

The average path duration (k-hop) is the average value of $PD_k(i, j)$ over the number of $k$-hop connected node pairs $P_k$. This results in the following:

$$\overline{PD}_k = \frac{\sum_{i=1}^{N} \sum_{j=i+1}^{N} P D_k(i, j)}{P_k}$$


4. **Fraction of connected time (k-hop):** This is the ratio of the total amount of time that a pair of nodes $i$ and $j$ are connected with the $k$-hop path throughout the simulation period to the amount of time that the two nodes coexist in the network. Mathematically,

$$FT_k(i, j) = \frac{\sum_{t=0}^{T} X_k(i, j, t)}{CT(i, j)}$$

where $CT(i, j)$ denotes the amount of coexisted time of nodes $i$ and $j$ in the network. In particular, it consists of the total connected and disconnected time of the $k$-hop path between nodes $i$ and $j$. Therefore, $1 - FT_k(i, j)$ will be the fraction of disconnected time of the $k$-hop path.

The average fraction of connected time (k-hop) is the average value of $FT_k(i, j)$ over the number of $k$-hop connected node pairs $P_k$. This results in the following:

$$\overline{FT}_k = \frac{\sum_{i=1}^{N} \sum_{j=i+1}^{N} FT_k(i, j)}{P_k}$$

Note also that the total connected time of a communication path is equal to the summation of all the connected durations between the two nodes in the simulation. Therefore, a communication path with a shorter average duration does not necessarily mean a smaller fraction of connected time as there could be more number of connections made throughout the simulation period. The combination of these metrics therefore allows us to gain a detailed understanding of the characteristics of the vehicle-based communications network.

**LONDON BUS NETWORK SIMULATIONS: RESULTS AND ANALYSIS**

In this section, we present the results and analysis of the London bus network simulations on the basis of the set of metrics presented in the previous section. We constructed a test network to include the real-world road topology and the actual geometry of three bus routes in the central London area. To demonstrate the importance of general transport models...
on connectivity studies, we present results of the bus network simulations with different densities of buses (as defined by the operating headway time between adjacent buses) and examine the influences of stop signs and background traffic on node connectivity. Last, we evaluate the distributions of the contact duration and intercontact time between buses.

We focused our discussion on parameters that were observed to have the most significant effects on node connectivity. It is part of ongoing research to investigate the effect of other traffic phenomena (e.g., bus priority) on vehicular networks in order to understand which elements must be considered and which can be neglected for a reliable evaluation of VANET performance.

**Model Configuration**

Several simulators, such as ns-2 (2009c), QualNet (2009d), and OPNET (2009a), have been developed for generic ad-hoc networks and modeling of the wireless channel. However, these do not support specific vehicle network topologies, whereas road traffic simulation models such as VISSIM (PTV, 2009), Paramics (SIAS, 2009) and SUMO (2009b) provide highly accurate traffic queuing and vehicle interaction models but do not typically integrate any aspects of intervehicle communication.

GrooveNet (Mangharam, Weller, Rajkumar, Mudalige, and Bai, 2006), jointly developed by Carnegie Mellon University and General Motors Corporation, is a hybrid simulator that enables communication between fully simulated vehicles, vehicles following real measured trajectories and between combinations of the two. It supports modeling of intervehicular communication within a real street map-based topography, and its modular architecture incorporates mobility, trip, and message broadcast models over a variety of link and physical layer communication models. Overall, we found that GrooveNet has competitive capability in the transport and communication aspects; we therefore used it for our simulations with customized modules. In particular, the original version of the simulator only supports TIGER map data in the United States; as a result, we developed the map data module that can read road network data in the United Kingdom from Ordnance Survey, and we acquired real bus route data from London Buses for three bus routes that pass through the region.

In particular, this included the coordinates (in terms of longitude and latitude) of the waypoints of the bus routes and those of the bus stops. The bus routes that we simulate are Routes 27, 31, and 88, with each route being split into two runs to represent the in-bound and out-bound journeys. Figure 3 shows how the three bus routes intersect, and Figure 4 shows the simulated road network in Camden Town with buses and background vehicles.

For the vehicle types, we considered buses and generic background vehicles in the simulation. In Figure 4, the solid circles denote buses with communication capability. These follow a bus trip model (on the basis of the real bus routes data) to move from their origins to destinations (bus terminals) with stops at intermediate bus stops. When the background traffic is included, there are circle-inscribed triangles that denote other vehicles without communication capability. These act as obstacles of the traffic flow of buses, and they use a sightseeing trip model to wander around the region.

The transmission range of buses is fixed at 200 meters in the simulations unless otherwise specified. All vehicles on the road use a car-following model (Rothery, 1992), where a vehicle will not exceed the speed of the vehicle in front. A vehicle that is determined to be a leader vehicle will use a general acceleration model. In the present study, we used the street speed mobility model, wherein vehicles always move within user-defined range of the speed limit of the road.

Table 1 shows basic information of the three simulated bus routes (e.g., length of the route, journey time, and peak hour frequency) according to Transport for London (2009b). In the simulations, we configured the street speed mobility model such that the leading speed of buses varies from 9 to 15 mph. With this speed setting, we have the average journey time taken for a bus to finish the whole route consistent with the Transport for London statistics (Transport for London, 2009b), as shown in Table 1. On the basis of the route length and the average journey time, we can further derive the average speed of buses in the

![Figure 3](image) Geometry of Routes 27, 31, and 88 that run through Camden Town, London (color figure available online).
simulations, which is between 7.7 and 9.3 mph, this again is consistent with the average London bus speed that ranges from 6.21 to 9.32 mph according to Figure 5.5 in the Transport for London (2008) report.

For the bus headway and schedule,

Table 1 shows that the peak hour frequency/headway of buses in the three routes ranges from 6 to 8 min. However, because we did not simulate all the bus routes that share the same road portions with the three bus routes, the simulated headway is considered the “aggregated” headway that captures the combined effect of all the buses operating through the routes, which should be smaller than the scheduled headway (6–8 min) of the three routes.

To estimate the aggregated headway and consider the combined effect of all the buses operating through the routes, we examined the number of buses that passed through bus stops X and Y in Camden High Street and bus stops T and U in Bayham Street (as shown in Figure 5) between 08:00 and 10:00 on a weekday morning, according to the bus information from Transport for London (2009a). For example, for the link in Camden High Street containing bus stops X and Y, 8 routes operate: 24, 27, 29, 31, 134, 168, 214, and 253.

Table 2 shows the number of buses on these routes passing through the link between 08:00 and 10:00 on a weekday morning as being representative of the peak bus density. We then derived the mean aggregated headway for the two links as 1.4 and 1.3 min. Hence, given the variability of on-street arrival times, we obtained the interarrival time of buses in the simulations varies in steps from 30 s to 5 min, which is reasonable to reflect the aggregated headway of the routes and provides a measure of the VANET performance should all buses be instrumented.

**Performance of Multihop Transmission in Bus Network**

Figure 6 shows the connectivity metrics (up to three hops) as a function of bus interarrival time of the bus network scenario with three bus routes (Routes 27, 31, and 88), all with two runs, and bus stops and traffic lights are included. We generated 300 buses for each route, in each direction, yielding 1,800 buses simulated in total.

Figure 6 shows that all of the metrics decrease as the bus density decreases (or interarrival time increases). However, the decrease in bus density only affects the stability of communication paths slightly, the average path duration varies by only about 7% according to Figure 6b. This suggests that the increased density of buses increases the frequency with which connections are formed, but it does little to alter the characteristics of each connection.
Figure 6 also shows a significant performance gap between single-hop links and multihop paths. For example, the average path duration and fraction of connected time of single-hop links are, respectively, about five times and three times larger than those of two-hop paths. For transmission with multiple hops, we can only achieve an average path duration of no more than 8 s, and the average fraction of connected time is below 0.6%.

Such poor multihop performance can be explained in two ways. First, the existence of two-hop paths requires more constraints to be satisfied than single-hop links, making them less likely to be maintained in the network. In particular, the existence of a single-hop link only requires that the receiver node be within the communication range of the transmitter node. However, a two-hop path requires the transmitter and receiver nodes to be within the communication range of the forwarding node and beyond the direct communication range of each other. Second, and as a consequence, multihop performance is more vulnerable to variations in the mobility pattern. Our findings tend to suggest that the bus mobility pattern does not favor multihop transmissions. This is in contrast with some other mobility scenarios; for example, an urban mobility model when considering a communications network formed by all the background vehicles in the Camden Town bus network, in which the private vehicles perform random walks in an urban grid. In this case,
we found that the fraction of connected time of multihop paths is larger than that of single-hop links when the node density is high.

We plotted in Figure 7 the path duration and fraction of connected time for a low density case (20 cars/km²) and a high-density case (100 cars/km²) of the urban mobility model of private vehicles. Figure 7a shows that single-hop links on average have a duration of about 45 s. As the node density increases, the duration that two-hop paths can achieve increases from 22% to 33% of the duration of single-hop links. It is interesting to note that when the node density is high, multihop paths’ average fraction of connected time even exceeds that of single-hop links (Figure 7b), which does not happen in the bus network. This appears to be the case because the closely packed urban grid topology and the presence of stop signs provide more contact opportunities between vehicles, communication paths thus have a greater number of connected periods on average, especially for multihop paths (e.g., three-hop paths have an average of 38 connected periods in the urban mobility model). Therefore, our results suggest that the performance of communication paths in VANETs depends highly on the mobility pattern of vehicles and vehicular density, and use cases and applications need to be designed according to the mobility characteristics of the end-user vehicles.

**Effect of Stop Signs and Background Traffic**

In addition to bus routes and interarrival time, several other macroscopic transport parameters have major influences on the connectivity graph, such as bus stops, traffic control signals, and the presence of background traffic. Figure 8 shows the simulation results of the three-bus-route network with a bus interarrival time of 5 min, including scenarios with (a) no transport factors considered; (b) with bus stops and traffic lights; and (c) with all bus stops, traffic lights, and background traffic. When a bus reaches a bus stop, it will stop for a random period of time that is uniformly distributed between some ranges (e.g., 15 s and 45 s). The mechanism of the traffic control signal used is simple, it consists of 30 s of green period followed by 30 s of red period. We divided the traffic lights in the road network into 100 groups, where traffic signals in the same group were synchronized. For the background traffic, we generated 100 background vehicles moving with the previously described sightseeing model along, and across, the bus routes.

Figure 8 shows that the number of connected node pairs increases by more than 40% when there are bus stops and traffic lights. The average single-hop link duration is also increased by more than 54%, which implies that a bus can contact with more neighboring buses throughout its journey and the communication links between them in general have better stability. This appears to be result of vehicles bunching up to form clusters at traffic lights and stops, with communication links formed between vehicles within a cluster usually lasting longer and being more stable.

To better characterize the effect of clustering brought upon by various transport factors, we examine the spatial density distribution of the bus network. Figure 9 depicts the time averaged density distribution of buses (communicating vehicles) along the three bus routes over a period of 2 hr with the consideration of different transport factors. The bus density is represented as the number of buses at a given point, normalized by a characteristic area of 0.13 km² associated with the assumed communicating radius of 200 m for these mobile nodes.

The figures show that even with no transport factors considered, density pulses exist at certain locations as a result of the road geometry (e.g., around sharp turns, loop routes, junctions, town centers where buses terminate), and such characteristics are retained even when other transport factors are introduced. With the introduction of traffic lights (dashed line) and stops (dash-dotted line), clustering of communicating vehicles can be seen. The density distribution is scaled up and distorted according to the location of stops and traffic lights, especially in regions where the stops are frequent.

However, the introduction of background traffic (dotted line) acts as a set of obstacles for the bus traffic, separating adjacent buses and redistributing buses along the routes due to the car-following mechanism. Figure 9 shows that the addition of background vehicles (dotted line) reduces the sharp density pulses (e.g., at 8 km on Route 27) along the bus routes, as this tends to prevent the bunching up of a large number of buses. Therefore, we observe in general a shorter path duration, a smaller
fraction of connected time and a smaller number of connected node pairs in Figure 8 when background traffic is applied in addition to stops and traffic control. As a result, stop signs and background traffic have fundamentally different influences on the density distribution of buses; the former favors while the latter hinders the clustering of communicating vehicles in the network.

Last, when considering traffic lights, stops, and background traffic altogether in the model, the density distribution is further boosted, and the density pulses characterized by the road geometry, stops, and traffic lights are magnified (except that certain sharp pulses are reduced by background traffic), which results in the black dot-marked line that is substantially different from the solid line. This result verifies the importance of capturing these macroscopic transport factors altogether in the simulation model and suggests that the inclusion of other transport factors should also be evaluated. Furthermore, although individual transport factor may have negligible influence on its own, when considered together there are complementary effects among them that greatly alters the spatial density of communicating vehicles.

**Contact Duration and Intercontact Time in Bus Network**

To successfully transmit data from one mobile node to another, the mobile node first needs to wait until it gets into the transmission range of the other node for data relay. Then, the mobile node will be able to relay the data to the other node during the period of time that they are connected (i.e., they are within the transmission range of each other). We refer to the former as the *intercontact time*, and the latter the *contact duration*. The concept of contact duration is similar to single-hop link duration introduced earlier, which is the average contact duration for all node pairs. For the intercontact time, it is defined as the time interval between two successive connection periods of a given pair of nodes.

The intercontact time between mobile nodes is typically assumed to be exponentially distributed and this has been numerically demonstrated for the most common mobility models in the MANET literature. However, recent empirical studies (Chaintreau et al., 2006) have provided evidence suggesting that the intercontact time distribution follows a power-law or Pareto distribution. Karagiannis et al. (2007) proposed through studies of empirical mobility traces a dichotomy hypothesis: power law decay of the intercontact time distribution up to a characteristic time, while beyond this characteristic time, the decay is exponential. Meanwhile, Cai and Eun (2007) proved, on the basis of commonly used random mobility models (random waypoint and random walk), that this discrepancy in the behavior of intercontact time between recent empirical results and the theoretical results is due to the effect of a finite boundary condition on the motion of the nodes.

These previous studies on intercontact time are primarily based on human mobility traces (e.g., conference, campus). To our knowledge, we are the first in the literature to examine the distributions of the intercontact time and the contact duration between vehicles that follow more advanced traffic models which capture general macro- and micromobility factors. The distributions are evaluated using their complementary cumulative distribution functions (CCDFs). From these we can determine...
Figure 9  Average density of communicating vehicles (buses) along Route 27 (a), Route 31 (b); and Route 88 (c) in a three-bus-route network. Bus interarrival time = 5 min. TL = traffic lights; BS = bus stops; BG = background traffic (color figure available online).
the probability that the contact duration (or intercontact time) is greater than or equal to a given amount of time; that is, \( P\{\text{contact duration/intercontact time } \geq t\} \). We define the contact duration or intercontact time CCDF as the CCDF of contact samples over all distinct node pairs in the network.

**Contact Duration**

We plotted in Figure 10 the contact duration CCDFs of the bus network on a semi-log scale with different bus density (or bus interarrival time). They are incorporated with the bus stops, traffic lights, and background traffic features, and we can see that they all exhibit a heavy tail. According to the figure, we can see that the CCDF decays less abruptly beyond a transition point at around 60 s, and it appears that the function mainly exhibits two portions of exponential decay. Because we can approximate or upper-bound the two portions of the CCDF on semi-log scale with a straight line, this indicates that the function decays at least exponentially fast.

To model the distributions more rigorously, we examine the value of the greatest discrepancy between the empirical cumulative distribution function (ECDF), \( F_e(x) \), and the hypothesized cumulative distribution function, \( F_h(x) \), such discrepancy is called the D-statistic, and is formally defined as follows:

\[
D = \max_s |F_e(x) - F_h(x)| \tag{7}
\]

As we aim to approximate the ECDF by certain hypothesized CDF (and not to prove that they are identical), we only examine the D-statistic value. If the value is sufficiently small, it indicates that the ECDF can be approximated by the CCDF.

As a result of the aforementioned observation, we tried to approximate the decay of the contact duration CCDF with exponential functions, \( Ke^{-ct} \), for some \( K \) and \( c > 0 \). We showed that piecewise exponential is a reasonable approximation for the contact duration distribution in bus network, the reader is referred to Table 3 for the values of \( K \) and \( c \) that approximate the function, and the corresponding \( d \).

In Figure 10, the turning point for the slope change remains at around one minute, we denote the turning point as the characteristic time. As a side note, we observe that the slope change in Figure 10 becomes less apparent as the bus density decreases. It appears that the tail of the solid line (5-min interarrival) can be approximated with a straight line in a log-log plot, suggesting that the contact duration CCDF tail gradually migrates from exponential to power-law decay when the bus density decreases. For some \( \alpha \) and \( t_0 > 0 \), a Pareto distribution has pdf \( f(t) = \alpha t_0^{\alpha} / t^{\alpha+1}, t \geq t_0 \). In particular, we found that the contact duration portion from 40 to 2,000 s of the 5-min interarrival case follows a Pareto distribution with \( \alpha = 3.85 \) and \( t_0 = 28 \) (D-statistic = 0.0088).

Although differing bus density gives rise to different slopes (after the turning point) of the contact duration CCDF, it appears that the characteristic time is not affected by the bus density. Therefore, we would like to explore the influence of other macroscopic transport elements on the distribution as well as the characteristic time. In particular, we compared in Figure 11 the contact duration CCDF of several bus network scenarios (30-s bus interarrival) with and without the consideration of stops (including bus stops and traffic lights) and background traffic. Figure 11 shows that bus stops and traffic control signals do have a significant influence on the characteristic time of the decay, in particular, without the consideration of stop signs, the characteristic time is reduced by half (from around 60 to 30 s); while background traffic mainly affects the slope of the second portion (after the turning point). It is interesting to note that background traffic lengthens contact duration when there are no stop signs (dotted line), but shortens contact duration when there are (solid line).

On the basis of these figures, it can be summarized that the first portion of the CCDF (from 0 to the turning point) is a function of traffic control/management, while the second portion (after the turning point) is a function of vehicular density. Actually, we found that the first portion mainly corresponds to contacts between vehicles moving in reverse direction, given that the links between them are relatively short (as a result of high relative speed) regardless of the node density. Traffic controls and stops lengthen the communication links between vehicles moving in opposite directions and, therefore, they are capable of delaying the characteristic time (the delay, which is about 30 s, also corresponds to the average stopping time of buses at stops and traffic lights). Alternatively, the second portion

### Table 3  K-S test results for different portions of contact duration CCDFs.

<table>
<thead>
<tr>
<th>Mobility Models</th>
<th>Portion (seconds)</th>
<th>( K )</th>
<th>( c )</th>
<th>D-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bus (interarrival: 30 s)</td>
<td>20 to 80</td>
<td>1.76</td>
<td>0.0461</td>
<td>0.0321</td>
</tr>
<tr>
<td>Bus (interarrival: 30 s)</td>
<td>100 to 1,500</td>
<td>0.07</td>
<td>0.0028</td>
<td>0.0061</td>
</tr>
<tr>
<td>Urban (100 cars/km²)</td>
<td>50 to 200</td>
<td>0.61</td>
<td>0.0118</td>
<td>0.0205</td>
</tr>
<tr>
<td>Urban (100 cars/km²)</td>
<td>200 to 3,500</td>
<td>0.134</td>
<td>0.0031</td>
<td>0.0061</td>
</tr>
</tbody>
</table>
portion mainly corresponds to contacts between vehicles moving in the same direction, which depends primarily on node density (which is affected by the bus density and background traffic density). However, when the node density is low, there is less of a distinction between the two regimes of the distribution, and traffic control passes into the dominating factor of this portion as well.

Intercontact Time

Figure 12 plots the intercontact time CCDFs of buses on a log-log scale (the 3- and 5-min curves are not plotted since intercontact samples are scarce for these cases), and again they exhibit a heavy tail. It appears in the figures that the dichotomy hypothesis (power-law followed by exponential decay) as proposed by Karagiannis et al. (2007) on the basis of real-life mobility traces still applies in the simulated bus network. We can observe the CCDF on a log-log scale roughly follows a straight line, which suggests a power-law decay; while beyond the characteristic time at about 1,000 s, the CCDF drops abruptly, and we find that it can be upper-bounded with a straight line in the semi-log plot, thus indicating the tail of the CCDF decays at least exponentially fast. The reader is referred to Table 4 for the values of $\alpha$ and $t_0$ in the Pareto distribution that approximate the function, and the corresponding D-statistic. The power-law coefficient $\alpha$ is dependent on the node density; the higher the density of communicating vehicles, the larger $\alpha$ is. Overall, the simulated bus network is consistent with the real-life mobility traces studied in Chaintreau et al. (2006) that the power-law coefficient $\alpha \leq 1$.

Once again, the bus density has negligible influence on the characteristic time of the intercontact time distribution. Therefore, we plot in Figure 13 several scenarios with and without the consideration of stop signs and background traffic. Similar to the contact duration, we can observe from the figure that the introduction of stop signs delays the characteristic time of the intercontact time distribution from about 500 to 1,000 s, and increases the power-law coefficient $\alpha$. It is because the characteristic time of intercontacts is governed by the bus journey time (assuming that buses sink all data upon arrival at terminals), the longer the bus journey, the larger the characteristic time, and the presences of traffic signals and stops will definitely lengthen the bus journey. The dash-dotted line indicates that traffic signals and stops increase the proportion of intercontact time that is less than 200 s and greater than 800 s, which once again is consistent with the clustering of vehicles brought upon by traffic controls. This is because links formed between vehicles moving in the same cluster can reconnect within a shorter period of time (<200 s) once they got disconnected, while links between vehicles divided into different clusters by traffic controls take much longer time (>800 s) to reconnect. The effect of background traffic alone on intercontact time is negligible, but in addition to the presence of stops and traffic lights, it increases the power-law coefficient $\alpha$, and generally reduces the intercontact time of communication links in the network (as indicated by the CCDFs that the solid line is always upper bounded by the dash-dotted line).

We have also examined the contact duration and intercontact time CCDFs of private vehicles moving with the urban mobility

<table>
<thead>
<tr>
<th>Mobility Models</th>
<th>Portion (seconds)</th>
<th>$A$</th>
<th>$t_0$</th>
<th>D-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bus (interarrival: 30 s)</td>
<td>50 to 1,000</td>
<td>1</td>
<td>10.57</td>
<td>0.0112</td>
</tr>
<tr>
<td>Bus (interarrival: 60 s)</td>
<td>50 to 1,000</td>
<td>0.84</td>
<td>10.1</td>
<td>0.0097</td>
</tr>
<tr>
<td>Urban (100 cars/km²)</td>
<td>100 to 2,000</td>
<td>0.581</td>
<td>18</td>
<td>0.0125</td>
</tr>
</tbody>
</table>

Table 4  K-S test results for various portions of intercontact time CCDFs. The empirical function is $\alpha t_0^{\alpha} t^{\alpha-1}$.
model. In general, we can observe similar patterns as those of buses, but the coefficients vary. For example, private vehicles have larger characteristic time than buses, which corresponds to longer contact duration and intercontact time between private vehicles on average. Table 3 and Table 4 summarize our findings.

Because contact duration and intercontact time characterize respectively the duration and the frequency with which packets can be delivered between mobile nodes, their tailed distributions have a direct effect on the actual performance and theoretical limits of opportunistic forwarding and routing algorithms in communication networks. Recent works (Bai et al., 2004; Karagiannis et al., 2007; Lee, Lee, Oh, and Gerla, 2007) that have attempted to analyze protocol performance in MANETs have assumed the distributions follow one single distribution (e.g., exponential). For example, Chaintreau et al. (2006) assumed that intercontact time is power-law distributed, and showed that when the power-law exponent \( \alpha \) of the intercontact time distribution is less than or equal to one, the mean packet forwarding delay is infinite for any opportunistic packet forwarding schemes (even for flooding). However, our results suggest that this is not the case in VANETs, the distributions have to be modeled in portions because there exist distinct transition points (or characteristic times) in the distributions. The existence of the following exponential tail may eliminate the issue of infinite packet forwarding delay under the power-law tail assumption. Nevertheless, the mean intercontact time is of the same order as the characteristic time, and thus the exponential tail should not be ignored.

Furthermore, the connectivity results obtained in this article can (a) serve as a fundamental building block for the development of synthetic mobility models in urban road network and (b) provide insights into the design of various communication protocols and networking functions. For example, according to Calegari, Musolesi, Raimondi, and Mascolo (2007), single-hop connectivity statistics (e.g., contact duration, intercontact time, node distribution) can be exploited to construct a connectivity graph, which is a collection of time-varying graphs of instant connectivity for each instant \( t \). In these time-varying graphs (one for each time instant), each (single-hop) link is either ON if the two nodes are connected, or OFF, otherwise. Once the temporal dimension is introduced via the time-varying graphs, delay-tolerant connectivity between any two nodes in the network can then be deduced by identifying the set of single-hop links that can bridge the two nodes in time. Hence, development and evaluation of delay-tolerant routing protocols and opportunistic packet forwarding algorithms can be carried out.

**IMPLICATIONS OF NODE CONNECTIVITY ON TRANSPORT SERVICES**

The characteristics of the interbus communications network influence the transport (and other) services that may be supported. In previous sections, we showed that real-time multihop connectivity is dramatically poorer than that of single-hop links, and we investigated the distributional properties and average values of contact duration and intercontact time between buses from extensive simulations. In all, these properties characterize the performance of the communications network and these characteristics may then be mapped against potential use cases of interest in order to identify appropriate applications. In this section, we briefly consider how these results obtained relate to a section of services that might be of interest to deploy within a bus-to-bus network. This selection is not exhaustive but is intended to illustrate how the communications performance can affect the system design.

Key performance requirements for an intelligent transport system include the connection availability, the data transfer rate and the end-to-end latency associated with the transfer of a given message packet. These properties are conditioned by the connectivity, the contact duration, and the intercontact time respectively. Different services have different requirements. In this article, we considered three services whose requirements are summarized in Table 5.

1. **An emergency video call to a control center**: This is a low-frequency occurrence but may happen anywhere in the network, at any time, and will require significant bandwidth and low latency if a call is made.

2. **In-service travel-time predictions**: In this case, a bus may be used as a probe vehicle to monitor the upcoming network conditions for the vehicles that follow. By passing information about the downstream journey time to a vehicle passing in the opposite direction, the knowledge may pass upstream and allow passengers waiting to board subsequent buses to more accurately project their onward journey times.
Table 5  Summary of protocol requirements for a selection of bus-to-bus VANET applications.

<table>
<thead>
<tr>
<th>Use Cases</th>
<th>Communications Objective</th>
<th>Data Rate Requirement</th>
<th>Data Latency Requirement</th>
<th>Viable?</th>
</tr>
</thead>
<tbody>
<tr>
<td>On-bus security alert</td>
<td>On demand streaming of video or voice</td>
<td>High for video, moderate for voice</td>
<td>Very low data latency required for seamless communications</td>
<td>NO</td>
</tr>
<tr>
<td>Traveler information on journey times</td>
<td>Transfer of travel time data from upstream buses to those following</td>
<td>Low</td>
<td>Must arrive in time to allow passengers to choose routes</td>
<td>YES</td>
</tr>
<tr>
<td>Bus lane parking enforcement</td>
<td>Periodic transmission of still images to identify offending vehicles</td>
<td>Moderate</td>
<td>Within 10 min to allow removal of vehicle</td>
<td>YES</td>
</tr>
</tbody>
</table>

3. Bus lane parking enforcement: Forward-facing cameras on the buses may be used for parking enforcement by capturing a still photograph of the offending vehicle. For critical routes, rapid transfer of this data would allow the removal of the vehicle, while a slower transfer would be sufficient to enable a penalty ticket to be issued to the registered owner.

The availability and latency requirements for service case 1 are challenging for an ad-hoc network. According to Figure 6b, real-time multihop connectivity is poor in the bus network (average path duration is less than 10 sec). In addition, Figure 9 illustrates the spatial variability in the connectivity as a function of the network characteristics. The lack of a continuously available communications channel makes a VANET inappropriate for this kind of real-time application if centralized intervention is required. However, when connected it is possible that relatively high bandwidth communications might be established within a local cluster of buses allowing transfer of video data to adjacent vehicles. To provide centralized data transfer, it may be useful to consider a hybrid network of fixed and mobile communications nodes such that roadside repeaters can act to fill in systematic gaps in the network. Alternatively, a network in which vehicles other than just buses participate may also be of interest.

For the second example use case, the travel-time information is required to travel back upstream. The simulation results presented in this article suggest that the frequency with which buses traveling in opposite directions form a communications link with an average link duration of more than 35 s is relatively high. This combined with the low data rate requirement suggest that such a system may be successfully deployed. In this context, the delay-tolerant connectivity is key, with messages remaining useful if they are forwarded through the network with sufficient speed to propagate back upstream. However, the potential short-term variability in the traffic conditions also suggests that there is an upper limit to this delay tolerance.

To examine this case further, we examined the delay tolerant connectivity of the bus network. A message with a lifetime of 10 min was broadcast from a bus at the middle of Route 27 in the three-bus-route network simulation (with traffic lights, stops, background traffic enabled). Each bus that received the message rebroadcasts it. We assumed the message size is small, so there is negligible transmission delay and overhead.

Figure 14 shows the (maximum) message penetration distance and fraction of buses reached by the message over time. The maximum penetration distance is a function of the size of the longest connected group of vehicles, and the fraction of buses reached is the ratio of the number of buses which have received the message via broadcast from vehicle-to-vehicle communication to the total number of buses that coexist in the network. From Figure 14a, we can also derive that the average message penetration rate of the bus network is about 6.5 m/s.

Figure 14a suggests that the message penetration rate is somewhat variable, and it may be that particularly congested areas of the network (where real-time travel time updates are more likely to be useful) are more critical to consider for this application. In such cases, the network topology, and in

![Figure 14](https://example.com/figure14.png)
particular the location of junctions and bus stops that facilitate the formation of bus clusters in relation to the congested parts of the network will condition the system performance. The final use case is comparatively simple to implement using a bus-based VANET as the data transfer requirements are relatively straightforward. With respect to our simulation results, the average contact duration and intercontact time between buses are respectively 46.85 s and 49.14 s. Assuming a data rate of 1 Mbps when a link is established, the transmission of 5.8-MB data can be supported per contact on average, which is sufficient for the transfer of multiple still images. Moreover, Figure 14a shows that the data latency requirement of 10 min allows the data to penetrate a distance of about 4 km, which is enough for the message to reach certain infrastructure nodes (e.g., located at bus stop) with wired backhaul in the network. Hence, it is likely that large amounts of data can be infrequently exchanged between buses, and this tends to support the parking enforcement application well.

In general, given the multihop connectivity among buses through the store-carry-forward (delay-tolerant) routing approach, a giant urban mobile communication infrastructure and probing system can be developed, which is expected to play an important role in supporting the delivery of various kinds of sensor and surveillance data. For example, collection and dissemination of pollutant data for environmental monitoring throughout the city, which is the main objective of the MESSAGE project (2009f).

CONCLUSIONS

Previous studies on node mobility and connectivity modeling often neglect real-world mobility constraints by adopting random mobility models. Moreover, none of them has considered mobile nodes or vehicles as different types with different mobility patterns. In this article, we established a more realistic simulation framework that takes account of various important transport factors and different vehicle types for evaluating connectivity in VANETs. This framework is used to explore the applicability of VANETs to the provision of a number of intelligent transportation system services. In particular, through a semirealistic simulation of a bus network in central London, we investigated the fundamental properties of various connectivity metrics in VANETs. In particular, we have shown that the distribution of the contact duration between buses follows a piece-wise exponential decay given that the bus density is high enough; while the intercontact time distribution exhibits a transition from power-law to exponential decay in the simulated bus network. To our knowledge, this is the first study in the literature that investigates the fundamental distribution of these connectivity parameters in an interbus communication network, and such knowledge can serve as input to connectivity trace generators for the development and evaluation of routing protocols and opportunistic packet forwarding algorithms in VANETs.

The effect of various transport factors on connectivity between vehicles has also been demonstrated. For example, we have found that stop signs and background traffic have fundamentally different influences on the density distribution of buses; the former favors while the latter hinders the clustering of communicating vehicles in the network, and hence they have substantially different effect on the path duration and fraction of connected time between buses. Traffic lights and stops also delay the transition point (or characteristic time) of the piece-wise distributions of contact duration and intercontact time, and traffic management (e.g., traffic lights, stops) and node density (e.g., interarrival rate, density of background traffic) characterize respectively different portions of the piece-wise distributions. These give us a key message that these transport factors must be modeled adequately when studying VANETs.

In addition, different types of vehicles have different mobility patterns, which could significantly alter the connectivity graph in intervehicle communication networks, and thus communication protocol performances. In general, we found that private vehicles moving in urban area with the sightseeing trip model exhibits better connectivity for multihop communications, especially when the node density is high. Alternatively, multihop paths have much poorer connectivity statistics than single-hop links between buses. It once again verifies that the mobility of buses must be modeled independently, as its unique mobility pattern brings upon distinct effect on node connectivity, which could affect design decisions in interbus communication networks. For example, given the relatively short multihop path duration between buses, a key message is that it is inappropriate to rely on using multihop transmissions to support real-time applications in interbus communication networks.

Connectivity evaluations carried out in this article is significant for the design decisions of a set of transport-related data dissemination services in real world. With regard to the connectivity metrics, we have quantified (in terms of data rate and data latency requirements) the feasibility of disseminating various types of data among buses. Although real-time applications such as video streaming between buses that requires relatively high data rate and low data latency might not be possible, some delay tolerant applications such as traffic information or pollutant and surveillance data dissemination among buses are viable.

As a future work, we aim to further develop our simulation models and consider more transport features to investigate the actual effect of other traffic phenomena on vehicular networks, in order to understand which elements must be considered and which can be neglected for a confident VANET study. Furthermore, we endeavor to validate our results with empirical data in order to more rigorously model node connectivity in VANETs, which will shed light on future studies and analyses of the capacity and delay performance of packet forwarding algorithms, and other networking functions in intervehicle communication networks.
REFERENCES


