Connectivity Modeling and Simulation for Vehicular Delay-Tolerant Networks (Postprint)

Authors: Bi Junlei, Li Zhiyuan

Date: 2018-05-18T00:00:00+00:00

Abstract

This study investigates connectivity modeling for vehicular delay-tolerant networks. First, it is assumed that the process of vehicles entering the road follows a Poisson distribution, and that vehicle speeds on the road follow a normal distribution. Subsequently, the distribution of inter-vehicle time headways based on the Poisson process is derived, and the connectivity probability of moving vehicles on the road is obtained accordingly. To verify the correctness and effectiveness of the proposed assumptions and connectivity model, traffic data from the European city of Luxembourg during the time period 7:30 a.m. to 8:30 a.m. is used as the experimental scenario. Theoretical calculations and simulation experiments are conducted on the Simulation of Urban Mobility (SUMO) platform to analyze the probability distribution of vehicle speeds, vehicle arrival rates, average number of vehicles on the road, and network connectivity probability. Experimental results demonstrate that the calculated values from the theoretical model are consistent with the simulation results, indicating that the proposed assumptions and connectivity model are reasonable and correct.

Full Text

Preamble

Title: Research on Connectivity Modeling and Simulation for Vehicle Delay Tolerant Networks

Authors: Bi Junleia, Li Zhiyuanb

Affiliation: Jiangsu University (a. Information Center; b. School of Computer Science & Telecommunications Engineering), Zhenjiang, Jiangsu 212013, China

Abstract: This paper investigates connectivity modeling for vehicle delay tolerant networks (VDTN). We first assume that the process of vehicles entering the road follows a Poisson distribution and that vehicle speeds on the road follow a normal distribution. Subsequently, we derive the inter-vehicle time headway distribution based on the Poisson process and use this to derive the connectivity probability of traveling vehicles on the road.

To verify the correctness and validity of the proposed assumptions and connectivity model, we use traffic data from Luxembourg City between 7:30 a.m. and 8:30 a.m. as our experimental scenario. We conduct theoretical calculations and simulation experiments on the probability distribution of vehicle speeds, vehicle arrival rates, average number of vehicles on the road, and network connectivity probability using the Simulation of Urban Mobility (SUMO) platform. Experimental results demonstrate that the theoretical model calculations align with simulation outcomes, confirming the rationality and correctness of the proposed assumptions and connectivity model.

Keywords: vehicle delay tolerant networks; network connectivity; vehicular traffic model; simulation of urban mobility

0 Introduction

The rapid development of short-range communication and intelligent transportation technologies, coupled with increasing demand for mobile vehicular services (including active safety and user entertainment), has drawn significant academic and industrial attention to Vehicle Delay Tolerant Networks (VDTN) as an emerging technology [1]. Unlike traditional Mobile Ad hoc Networks (MANET), VDTN employs opportunistic communication, resulting in intermittent connectivity. References [2–6] have studied routing and data forwarding in VDTN, implementing various routing metrics such as node geographic location, link quality between nodes, and next-hop selection based on historical encounter records, leading to greedy-strategy-based VDTN routing optimization algorithms. While these works enhance the probability of opportunistic encounters through prediction mechanisms and related strategies, vehicle connectivity in VDTN environments remains a critical technical challenge for improving data forwarding success rates. For instance, geographic information-based routing essentially selects the nearest node for data forwarding, fundamentally expecting that one-hop distance between communicating nodes falls within their communication range. Furthermore, in various VDTN applications, network connectivity between road vehicles can directly or indirectly reflect link quality conditions.

References [7–9] have studied topological characteristics of Vehicular Ad hoc Networks (VANET) using connectivity as a metric. Specifically, reference [7] analyzed how vehicle density, path loss exponent, and fading factors affect network connectivity. Reference [8] examined vehicle mobility models and trajectories, concluding that traffic "hotspots" and traffic light-induced clustering behaviors enhance network connectivity while non-uniform node distribution increases VANET centrality. Reference [9] assumed that "inter-vehicle headway follows an Erlang distribution" and modeled VANET connectivity accordingly, though this assumption lacks sufficient statistical validation from traffic data and mathematical proof. Consequently, in-depth research on VDTN connectivity modeling with validation based on real traffic data is necessary.

This paper focuses on VDTN connectivity for vehicles traveling in the same direction, as such scenarios facilitate successful data forwarding. We first assume that vehicles entering a lane follow a Poisson process with parameter and derive that inter-vehicle headway follows an exponential distribution. Building upon this, we investigate connectivity probability between vehicles on the lane. Finally, we validate the proposed connectivity probability model using the Simulation of Urban Mobility (SUMO) platform, selecting the representative medium-sized European city of Luxembourg for map and parameter data.

---

1 Network Model and Assumptions

Consider a road of length L, where road width is negligible compared to inter-vehicle communication distance. As shown in Figure 1 [Figure 1: see original paper], Xi represents the distance between the first vehicle and the observation point at time t=0, while Xn represents the distance between the nth and (n-1)th vehicles from the observation point at t=0. R denotes the vehicle node communication range.

We establish two fundamental assumptions:

a) Vehicle speeds v on the road are mutually independent, with speed frequencies following a normal distribution with parameters (, ^{2}) [10,11].

b) The process of vehicles entering the lane follows a Poisson process with parameter , where represents the average number of vehicles entering the road per unit time [12,13].

2.1 Inter-Vehicle Headway Distribution Based on Poisson Process

Inter-vehicle headway plays a crucial role in network connectivity modeling, defined as the time interval between successive vehicles passing a road cross-section (the observation point in Figure 2 [Figure 2: see original paper]) while traveling in the same direction. For a Poisson process with parameter , let N(t) denote the number of vehicles that have arrived by time t. According to the Poisson process definition, the probability of n vehicles arriving in a time interval of length t at any moment h can be expressed as Equation (1).

Let T represent the arrival time of the first vehicle at the road observation point, and T represent the inter-arrival time between the (n-1)th and nth vehicles. The time sequence {T } forms the headway sequence.

Let event A represent the first vehicle arriving at the observation point after time t. Event A occurs if and only if the Poisson process has no vehicles passing during the time interval [0, t], as shown in Equation (2). Consequently, T follows an exponential distribution with mean 1/ .

We can then derive the distribution of T , as shown in Equation (3). This demonstrates that T also follows an exponential distribution with mean 1/ and is independent of T . Repeating this derivation process shows that inter-vehicle headway follows an exponential distribution with parameter , as expressed in Equation (4).

2.2 VDTN Network Connectivity Modeling

Let v represent the speed of each vehicle on the road. All vehicles with speed v constitute vehicle subset C . Let L be the length of each lane. X represents the distance between adjacent vehicles in subset C at time t=0, where X ^{1} denotes the distance between the first vehicle in C and the observation point, and X (n 2) denotes the distance between the nth and (n-1)th vehicles from the observation point in C . T represents the inter-arrival headway between adjacent vehicles in subset C , where T ^{1} denotes the arrival time of the first vehicle in C at the observation point, and T (n 2) denotes the inter-arrival headway between the nth and (n-1)th vehicles from the observation point in C .

As established above, the arrival process of vehicles in subset C at the observation point follows a Poisson process with parameter , as shown in Equation (5). Therefore, the distances X between adjacent vehicles in C are independent and identically distributed, following an exponential distribution with parameter / , as derived in Equation (6).

Similarly, X also follows an exponential distribution with parameter / and is independent of X . Extending this reasoning, all X follow independent exponential distributions with parameter / , as shown in Equation (9).

Based on Assumption (a) from Section 1, vehicle speed v follows a normal distribution N(, ^{2}), where is the mean speed and is the standard deviation, with probability density function given by Equation (10). Let v_min and v_max represent the minimum and maximum speeds in the current lane, respectively. Combining Equations (9) and (10), the probability of vehicle speed v over the entire speed interval [v_min, v_max] is given by Equation (11).

The cumulative distribution function of inter-vehicle distance can then be derived as Equation (12). The average vehicle density on the road is given by Equation (13), from which we obtain the average number of vehicles N_average on the road, as shown in Equation (14).

When the inter-vehicle distance between two nodes is less than or equal to the communication distance R, the vehicles are considered connected. This yields the network connectivity probability formula for N_average vehicles on a road segment, which represents the network connectivity probability studied in this paper, as expressed in Equation (15).

While we could extend this single-road connectivity probability to model network connectivity across an entire road network, such calculation lacks practical significance for VDTN data forwarding. Instead, we focus on computing network connectivity probability along paths from source to destination nodes, which reflects real-world data forwarding scenarios. As illustrated in Figure 2 [Figure 2: see original paper], infrastructure at intersections acts as a coordinator. When a source node S needs to send a message, it requests the nearest intersection infrastructure, providing its own location and the destination node' s location. The infrastructure computes connectivity probabilities for all possible paths to the destination' s road segment and feeds back the path with maximum network connectivity probability to the source node.

The detailed calculation method is as follows: Let P_i represent the network connectivity probability in different road segments, computed using Equation (15). The network connectivity probability along a transmission path can then be calculated using Equation (16), where P_c is the network connectivity probability for the path from source to destination, R is the set of roads, and P_i is the connectivity probability for each road segment R_i.

Figure 2 shows that source node S can forward data to destination node D via two paths: the shortest path R1→R4 or the alternative path R2→R3→R4. The connectivity of path R1→R4 depends on whether the two vehicles connected by the dashed segment in road R1 are within each other' s communication range. This occurs only when the following vehicle' s speed exceeds the leading vehicle' s speed for a sufficient duration. In contrast, vehicles on road segments R2→R3→R4 remain continuously connected, making this the preferred routing path.

3.1 Simulation Tool Introduction

The Simulation of Urban Mobility (SUMO) [14] is an open-source, microscopic, multi-modal traffic simulation software developed by the German Aerospace Center (DLR) since 2000. SUMO was designed to provide traffic research organizations with a tool for implementing and evaluating their algorithms. Its key advantages include: (a) support for multiple network formats including VISUM, XML, and OSM; (b) microscopic routing with individual vehicle routes enabling dynamic user assignment; (c) high portability using only standard C++ libraries; (d) high interoperability through XML data formats; and (e) fast execution capable of managing networks with tens of thousands of streets. SUMO has become the standard simulation platform for vehicular traffic researchers.

3.2 Experimental Environment and Implementation Description

We employ the Luxembourg SUMO Traffic (LuST) scenario [14] as our simulation environment, as shown in Figure 3 [Figure 3: see original paper]. LuST provides pre-configured scenario parameters including road topology and vehicle mobility patterns, offering a solution that meets simulation requirements in terms of scale, realism, and duration. Geographically located in Luxembourg City—a medium-sized European city with representative urban road topology —LuST incorporates realistic daily traffic demands and mobility patterns, enabling accurate full-day traffic simulation for the Luxembourg region.

We selected partial segments from two highways in LuST as experimental observation sections, with each segment' s entrance designated as an observation point. To validate the two basic assumptions defined in Section 1, we deployed Instantaneous Induction Loops detectors at each observation point using SUMO to collect statistics including vehicle passage times and speeds, thereby verifying whether speed frequencies follow a normal distribution and whether vehicle arrivals constitute a Poisson process. Figure 4 [Figure 4: see original paper] shows one such observation segment during simulation, with magenta squares representing the deployed detectors.

3.3 Experimental Results and Analysis

1) Vehicle Mobility Model Validation and Analysis

Figures 5 [Figure 5: see original paper] and 6 [Figure 6: see original paper] validate whether LuST traffic data conforms to the basic mobility model assumptions from Section 1. Detectors at observation points collected speeds of all passing vehicles across 300 observation runs. Figure 5 presents statistical results for one observation point, showing vehicle speeds distributed between 8 m/s and 18 m/s with frequencies following a normal distribution within this interval, thereby validating Assumption (a) regarding normal speed distribution.

Additionally, detectors captured vehicle arrival times at observation points. Figure 6 shows statistical results for a 1 km observation segment. When dividing the 7:30 a.m.–8:30 a.m. observation period into 60-second intervals (e.g., 7:30–7:31 a.m., 7:31–7:32 a.m., ···, 8:29–8:30 a.m.), vehicle arrival counts fluctuate around 7.86 (the red dashed line in Figure 6). This confirms that the vehicle arrival process follows a Poisson distribution with parameter = 0.131 vehicles per second, validating Assumption (b).

During each 1-hour observation, SUMO' s fcd output recorded detailed scene information for every simulation frame (default: 60 frames/minute), including all vehicle positions. From this data, we first counted vehicles on each observation segment per frame, then computed the average number of vehicles per observation across all frames to obtain N_average. The blue zigzag curve in Figure 7 [Figure 7: see original paper] shows the per-observation average vehicle count across 300 runs, with the blue solid line representing the mean of these averages. The red dashed line indicates the theoretical average vehicle count computed using Equation (14). The close match between experimental and theoretical values validates the correctness and accuracy of our theoretical calculation for average vehicle density.

2) Network Connectivity Theory Validation and Analysis

We validated network connectivity probability estimation by observing two selected road segments in SUMO. During each observation, we examined per-frame vehicle position data to check connectivity status, yielding 3,600 connectivity states per observation. If road segment 1 exhibited k connected states during the ith observation, its connectivity probability was k/3600. The mean connectivity probability across 300 observations defined the segment' s vehicle connectivity rate.

Figure 8 [Figure 8: see original paper] compares experimental and theoretical network connectivity for two observation segments: Road 1 (2.4 km) and Road 2 (1 km). Using measured average speeds, speed standard deviations, and vehicle arrival rates for each segment, we computed theoretical connectivity probabilities via Equation (15) with communication radius R varying from 0–600 m (vehicles within distance R were considered connected). The experimental and theoretical curves match closely, validating our network connectivity model. Connectivity probability grows exponentially with communication radius R, exceeding 80% when R > 400 m and approaching stability as R continues to increase. These results confirm the consistency between experimental and theoretical network connectivity, validating the exponential inter-vehicle distance distribution and demonstrating that a robust connectivity model provides crucial theoretical guidance for routing and data forwarding design.

---

4 Conclusion

This paper models and simulates network connectivity in VDTN environments. Our primary contributions include: (1) deriving inter-vehicle headway distribution based on Poisson process assumptions for vehicle arrivals and normal distribution assumptions for vehicle speeds; (2) rigorously deriving network connectivity probability through mathematical analysis, showing that connectivity depends on vehicle speed v, arrival rate , communication distance R, road length L, and vehicle density ; and (3) validating the proposed mobility and connectivity models using the SUMO simulation platform with real traffic data from medium-sized Luxembourg City during 7:30 a.m.–8:30 a.m.

Experimental results validate both basic assumptions through analysis of vehicle speed distribution and arrival rates, confirming their rationality and correctness. Simulations of average vehicle count and network connectivity probability demonstrate consistency between theoretical calculations and experimental results. This work provides essential mobility and theoretical model references for future VDTN routing and data forwarding research based on network connectivity.

References

[1] Pereira P R, Casaca A, Rodrigues J J, et al. From delay-tolerant networks to vehicular delay-tolerant networks [J]. IEEE Communications Surveys & Tutorials, 2012, 14 (4): 1166-1182.

[2] Burgess J, Gallagher B, Jensen D D, et al. MaxProp: routing for vehicle-based disruption-tolerant networks [C]// Proc of the 25th International Conference on Computer Communications. [S. l.] : IEEE Computer Society, 2006: 1-11.

[3] Soares V N, Rodrigues J J, Farahmand F. GeoSpray: a geographic routing protocol for vehicular delay-tolerant networks [J]. Information Fusion. 2014, 15: 102-113.

[4] Khabbaz M J, Fawaz W F, et al. Probabilistic bundle relaying schemes in two-hop vehicular delay tolerant networks [J]. IEEE Communications Letter, 2011, 15 (3): 281-283.

[5] Togou M A, Hafid A, Khoukhi L. SCRP: stable CDS-based routing protocol for urban vehicular Ad hoc networks [J]. IEEE Trans on Intelligent Transportation Systems, 2016, 17 (5): 1298-1307.

[6] Alsharif N, Cespedes S, Shen X. iCAR: intersection-based connectivity aware routing in vehicular Ad hoc networks [C]// Proc of IEEE International Conference on Communications. [S. l.] : IEEE Computer Society, 2013: 1-5.

[7] 冯慧芳, 王瑞. 衰落信道下车载自组织网络连通性分析 [J]. 计算机工程与应用, 2016, 52 (18): 133-138.

[8] 杨卫东, 冯琳琳, 刘伎昭, 等. 车载自组织网络中网络连通特性研究 [J]. 通信学报, 2012 (s1): 48-52.

[9] 陈思敏, 赵海涛, 朱洪波, 等. 车载通信的网络连通性建模 [J]. 应用科学学报, 2017, 35 (1): 63-70.

[10] Yousefi S, Altman E, El-Azouzi R, et al. Analytical model for connectivity in vehicular Ad hoc networks [J]. IEEE Trans on Vehicular Technology, 2008, 57 (6): 3341-3356.

[11] El-Atty S M A, Stamatiou G K. Performance analysis of multihop connectivity in VANET [C]// Proc of the International Symposium on Wireless Communication Systems. [S. l.] : IEEE Computer Society, 2010: 1-5.

[12] Wu C, Ji Y, Liu F, et al. Toward practical and intelligent routing in vehicular Ad hoc networks [J]. IEEE Trans on Vehicular Technology, 2015, 64 (12): 1-12.

[13] Jia D, Lu K, Wang J. On The network connectivity of platoon-based vehicular cyber-physical systems [J]. Transportation Research Part C Emerging Technologies, 2014, 40 (1): 215-230.

[14] Codeca L, Frank R, Engel T. Luxembourg SUMO traffic (LuST) scenario: 24 hours of mobility for vehicular networking research [C]// Proc of International Conference on Vehicular Networking. [S. l.] : IEEE Computer Society, 2015: 1-8.

Note: Figure translations are in progress. See original paper for figures.