RESEARCH ARTICLE OPEN ACCESS

Large Scale Urban Vehicular Network Framework With User Level Mobile Node Based Optimal Content Delivery

C.Mani MCA., M.E.*, K.Karuppusamy**
*Associate Professor, Department of CSE, Nandha Engineering College (Autonomous), Erode, Tamilnadu, India.
Email: cmanimca@gmail.com
** Final MCA, Department of MCA, Nandha Engineering College (Autonomous), Erode, Tamilnadu, India.
Email: karuppusamy2141@gmail.com

****

ABSTRACT:

Gathering extensive public data from the IoT devices scattered throughout a city may be a significant challenge in a smart city. In this paper, a novel urban vehicle network we call the location -based urban vehicle network (LUV), is proposed to perform the non-real time data gathering task in smart cities. Different from the foremost works in-vehicle networks, the inquiry on the real-life 8900 private cars trace data in Changsha, China, compels us to specialise in the parked vehicles and therefore the parking places, instead of on the moving cars and the urban roads. The location-based mechanism not only provides more reliable and predictable wireless connections but also dramatically simplifies the system topology. It ensures that the vehicle network deployed on an intricate metropolitan area reaches the desired scale for gathering data.

Keywords —**Vehicular network, Internet of Things, scalability, smart city.**

****

I. INTRODUCTION

Nowadays, the smart city has attracted a tremendous amount of interests from government, academia, and industry [1], [2]. In this field, connecting everything during a city and sensing every corner of the town are going to be accessible if meeting the booming communication demands from the web of Things (IoT) [3]. The current estimates of about 20 billion of IoT sensors are connected, and this number will reach 50 billion by 2020 [4]. The Fifth Generation (5G) wireless networks are developing as the network solution of Smart City to connect the billions of IoT devices [5], [6].

A. MOTIVATION

In a smart city, the non-real-time urban IoT data collected over a period are converted to the usable information or knowledge for daily city operation and long-term urban planning, and the real-time IoT data are utilized to watch the urban environment for rapidly responding the varied emergencies [7]. In the scene of gathering non-real-time IoT data, there is no significant difference in performance between the high-speed telecom communication networks (Cable/5G) and the delay tolerant network (DTN), which is usually considered as a short lived emergency alternative for the destructed communication networks by natural disasters or military efforts [8].

B. CHALLENGE

More connected vehicles signify more resources to be utilized and better network performance when the cars are treated because the potential communication resources and

networked for gathering IoT data. As long as there are many vehicles within the modern metropolis, the size of the urban vehicular DTN should reach an equivalent level.

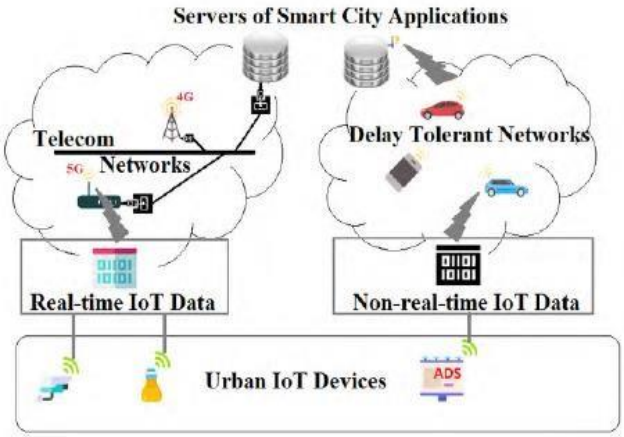


FIGURE 1. Urban IoT data transmission with the telecom networks and the DTNs.

Meanwhile, the general size of traditional VANETs can hardly be scaled up to large-scale. A decade ago, when the vehicle was just a tool of transport for people and cargo, Vehicular Ad-hoc Networks (VANETs), a kind of vehicle-based DTN, were first proposed as a promising approach for future intelligent transportation (ITS). Since VANETs are suggested to assist road vehicle driving, VANETs only connects the on-road vehicles. The assigned purpose of VANETs implies that VANETs nodes are always in motion.

C. METHODOLOGY

In this paper, firstly, based on the new purpose of IoT, we simplify the network topology to improve the network scalability. Secondly, we introduce the external network scheduling to scale back the system overhead on the large-scale vehicular DTN node.

To design a large-scale vehicular DTN framework, the properties of urban vehicles the researchers should fully utilize.

D. CONTRIBUTIONS

In this paper, consistent with the urban vehicular traffic network and a big amount of real trace data of privately-owned vehicles, detailed features of the characteristics of the cars are extracted and quantified with mathematic models. a completely unique vehicle activity model is presented to explain the activity pattern of urban privately-owned vehicles. Supported the activity model, we present a location-based urban vehicular network framework (LUV) for gathering local IoT data.

II. URBAN VEHICLES & VEHICULAR TRANSPORTATION NETWORK

In this section, we analyse the types of urban vehicles, and the existed urban vehicle transportation network. We aim to find out the factors which bring millions of urban cars out of chaos. By utilizing these factors, we can build a large-scale urban vehicle network.

A. TYPE OF URBAN VEHICLES

Urban vehicles can be characterized into three categories.

TABLE 1. Comparison of the three types of urban vehicles.

Urban Vehicle	Total weight	Type	Random-ness	Relationship of daily trips	Prediction method
Bus	Small	Fixed	Low	Duplication	/
Private vehicle	Dominate	Regular	Middle	Dependence	Bayesian decision
Taxi	Small	Roaming	High	Independence	Markov chain

1) FIXED ROUTE TYPE

Typical samples of this sort of vehicles are buses serving as public transportation means. They usually have fixed routes and also set schedules. Certain VANETs have centered design on this type of vehicles owing to regularity and predictability of their movement patterns [20].

2) ROAMING TYPE

Typical examples of this type of vehicles are taxis. A notable feature of this type of vehicles is that their moving routes are seemingly random. Their current path is independent of their past tracks. Often research VANETs models roaming type vehicle with Markov chains.

3) REGULAR TYPE

Often overlooked in the existing study are privately-owned vehicles in urban settings, possibly due to the problem of obtaining real trace data. We term this regular type as these vehicles are the most common in everyday life. It is also more complicated because the states of the vehicles exhibit a mixture of certain randomness and repetitiveness. Researchers have used Bayesian decision models for the predicting of the states of the regular type vehicles. Table 1 provides a comparison of the three types of vehicles. As we discussed above, quantitatively, privately-owned vehicles are typically the dominant type in the most metropolis of the world today. While buses and taxis mainly serve as complementary roles of municipal vehicles. To understand the essential feature of urban vehicles, we prefer to study the characteristics of private cars. To achieve this goal, we present a comprehensive analysing of privately-owned vehicles in the next section.

B. URBAN VEHICULAR TRANSPORTATION NETWORK

The studying of the existing urban vehicular transportation network helps us understand the rules of the vehicle in an urban environment to design a new type of large-scale urban vehicle network.

In a vehicle trip, a vehicle loads passenger/cargo before leaving its departure place. Then the car moves on the roads and unloads its passenger/cargo after arriving at its destination place. The purpose of a privately-owned vehicle trip is to transfer people/cargo from one place to another. The departure and destination places are fixed before the vehicle starts its tour, while the drivers change the road paths temporarily according to the variable road conditions.

III. EMPIRICAL DATA ANALYSIS

Vehicle network study from the perspective of private vehicles is rare due to the lack of real-life traces of privately owned vehicles. In this section, we offer a study of a broad set of traces of privately-owned vehicles. First, we give a brief overview of the monitor dataset source. We next present the primary stationary metrics embedded in

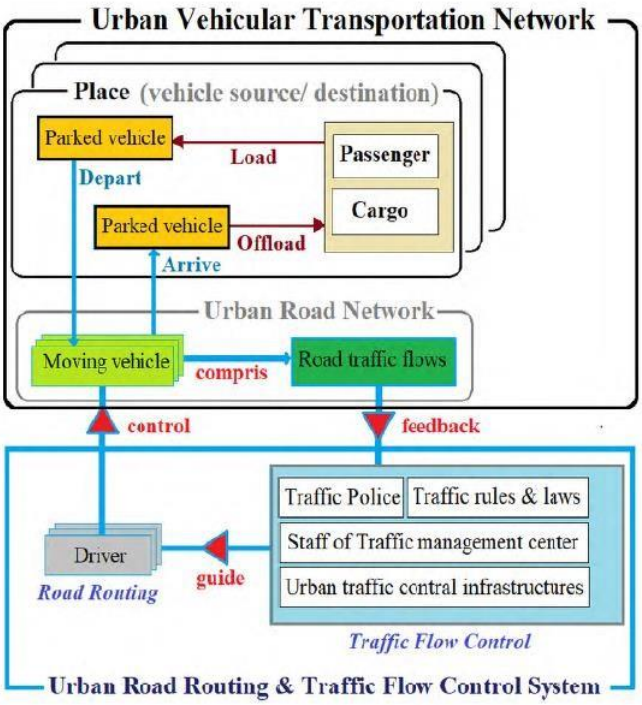


FIGURE 2. Urban vehicular transportation network.

the monitor data sets, including average daily parked time, all-day parking ratio, and residential area. Then we carry out a detailed statistical analysis of the pre-treated dataset and acquire empirical metric values.

A. MONITORING DATA SET

The monitoring dataset we study is generated by the private vehicle monitoring system (PVMS), which installed on 8900 privately-owned vehicles in Changsha, China. The PVMS provides remote vehicle monitoring service to privately-owned vehicles. The essential functions of PVMS include GPS location tracking, theft alarm, and remote device diagnosis. A vehicle terminal is mounted on the target vehicle for real-time monitoring. It collects real-time vehicle data and sends them to a central monitoring platform through GPRS networks. The system architecture of PVMS is illustrated in Figure 3.

B. AVERAGE DAILY PARKED TIME

With the statistics of average daily parking time of privately-owned vehicles in Changsha, we can learn the empirical probability of vehicle parking per day. Correspondingly, privately-owned vehicles daily running time is 1.37 hour/day, or 82 min/day.

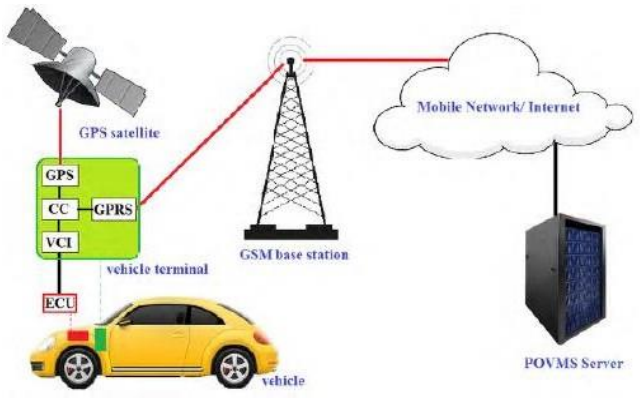


FIGURE 3. System architecture of PVMS.

The average daily parked time of privately-owned vehicles in Changsha is about 22.63 hours/day.

C. ALL-DAY PARKING RATIO

If a vehicle did not move in a day, then the vehicle has an All-day parking state. All-day parking is the most steady and predictable state. It is usually taken as an extreme and rare circumstance, generally

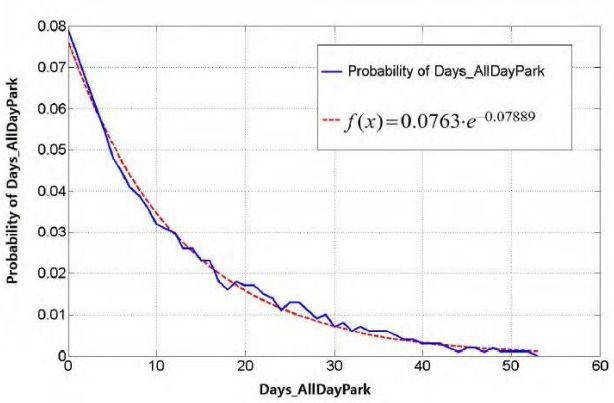


FIGURE 4. PDF of Days All Day Park & exponential distribution.

Ignored in most vehicle network studies. However, our data set indicates that the average daily parking time counts for 95% in a day. A reasonable inference is that the scale of all-day parking states of vehicles in the urban environment more common than we have thought.

To study this, we introduce one key metric, All-day parking Ratio (R_ADP), to describe the global privately-owned vehicle All-day parking situation in the urban environment.

We define R_ADP as

$$\text{R\_ ADP D} = \frac{Days\_All\ Day\ Park}{Days\_statistics} \qquad (1)$$

Days_statistics represents the statistical period, and *Days_AllDayPark* represents the number of the all-day parking days in the statistical period. Based on the vehicles' monitoring data statistics, we obtain the distribution of *Days_AllDayPark* in Figure.4. The plots follow a clear exponential distribution.

Let *X* be a random variable as *Days_AllDayPark* over the 61 days (*Days_statistics*) that has an exponential distribution with the mean *E*(*X*) and the variance *VAR*(*X*), i.e., *X* _ *Exp* (_).

To identify the exponent constant λ of the exponential distribution of all-day parking day, we apply polynomial regression. The validation of the regression is measured by the coefficient of determination (*R_square*), and the root mean squared error (*RMSE*)

$$R\_square = 1 - \sum_{i=1}^{n}(x_i - \hat{x}_i)^2 / \sum_{i=1}^{n}(x_i - \bar{x})^2 \qquad (2)$$

where x_i denotes the sample value with the mean $\hat{x}$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2} \qquad (3)$$

We apply this exercise to the plots in the Figure.4 where the distribution of all-day parking radio is very well approximated (*R_square* = 0.9942; *RMSE*D = 0.0016) by an exponential distribution *Exp* (0:07889).

$$\Rightarrow E(X) = \frac{1}{\lambda} = 12.68, \quad VAR(X) = \frac{1}{\lambda^2} = 160.68 \qquad (4)$$

Let *R* be a random variable as R_ADP, we have

$$\Rightarrow E(R) = E(\frac{X}{Days\_statistics}) = \frac{1}{Days\_statistics} \cdot E(X) = 0.2079 \qquad (5)$$

The expectation of R_ADP in Changsha city is 20.79%.It indicates that on the average onefth of privately-owned vehicles are in the state of all day parking

D. RESIDENTIAL AREA

By further analyzing the states of all-day parking, we observe that the locations of all-day parking of

vehicles are very predictable and varying little. These mostly are the places of residence of the owners. Being consistent with our common sense, most of the people only have one residential house. The monitor data shows that the residential district of a vehicle is sole. Additionally, these places have the highest daily visit frequency and the most prolonged parking periods, about 14.6 hours per day.

IV. MODEL ANALYSIS

In this section, we propose our vehicle activity model for the large-scale urban vehicle network.

A. NOTATIONS

We define the following notations.

Definition 1: The region of Urban is defined as U

Definition 2: The vehicles in the region *Re* are defined as *VU*, the amount of the vehicles in the region is defined as *Num_VU*, and the vehicle *i* is defined as

$$v_i \in V_U, \quad 0 < i \leq Num\_V_U$$

Definition 3: The parked areas which vehicles gathered in the region U are defined as P, P€U, the amount of the parked areas in the region is defined as *Num_PU*, and the parking area *j* is defined as

$$p_j \in P, \quad 0 < j \leq Num\_P_U$$

Definition 4: The residential place of the vehicle *vi* is defined as *RP_vi € P*

Definition 5: The time slots of a day are defined as *TS*, the amount of the time slots of a day is defined as *Num_TS*, and the time slot *k* is defined as

$$ts_k \in TS, \quad 0 < k \leq Num\_TS$$

Definition 6: The parked/active status of the time slot *tsk* of the vehicle *vi* is defined as *status_tsiK*

$$status\_ts_k^i = \begin{cases} 1, & vehicle\ i\ parked\ at\ the\ time\ slot\ k \\ 0, & vehicle\ i\ with\ motion\ at\ the\ time\ slot\ k \end{cases} \quad (6)$$

Definition 7: The daily parked time of the vehicle *vi* is defined as *PTi*

$$PT_i = \sum_{k=1}^{Num\_TS} Status\_ts_k^i \quad (7)$$

Definition 8: The average daily parked time of the vehicles *VU* with the time slots is defined as *ADPTV TS*

$$ADPT_{TS}^V = \frac{1}{Num\_V_U} \sum_{i=1}^{Num\_V_U} \sum_{k=1}^{Num\_TS} Status\_ts_k^i \quad (8)$$

B. TIME UNIT OF TIME SLOT

To observe and describe the daily activities of a vehicle, we divide a day into continuous time slots with a specied time unit. The smaller the time unit is, the more precise the results are. On the opposite hand, to urban VANETs, a system with many nodes, a smaller unit of time means massive overhead in data processing. Considering that privately owned vehicles are not on the road for 95 percent of the time, there's an opportunity of reducing the system overhead and also maintaining the accuracy of the results by setting coarse grained time unit.

In this paper, we attempt to set a coarser unit of time than 10 minutes for lower system complexity and overhead. We place 1 hour as an essential time unit and divide a day into 24 slots. With the data set from 7520 privately-owned vehicles spanning 61 days, we obtain the distribution of the entire number of daily parked slot s (the time slot unit is 1 hour), as shown in Figure.5.

The average daily parked time average *ADPT*1*h* from the 7520 privately-owned vehicles spanning 61 days is

$$ADPT_{1h} = \frac{1}{61 \times 7520} \sum_{d=1}^{61} \sum_{i=1}^{7520} \sum_{k=1}^{24} Status\_ts_k^i = 20.54 \quad (9)$$

Combined with *ADPT*10*m* (the time slot unit is 10 minutes) is 22.63 hours/day, the following equation can obtain the coefficient degree of *ADPT*1*h*.

$$C_{ADPT_{1h}} == 1 - \frac{|ADPT_{10m} - ADPT_{1h}|}{ADPT_{10m}} = 90.76\% \quad (10)$$

The result shows that one hour is an appropriate time unit to observe and describe the daily parked events of vehicles in urban vehicle network.

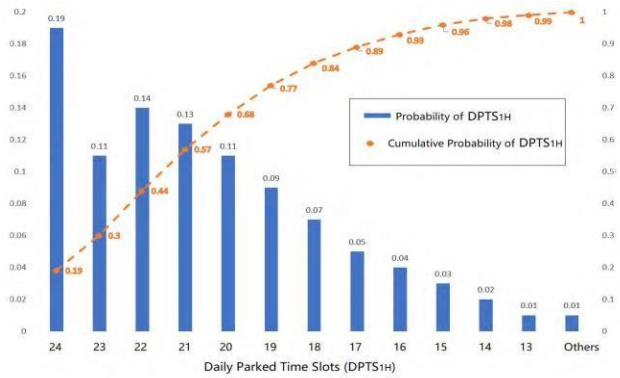


FIGURE 5. Probability distribution of the total number of DPTS1H.

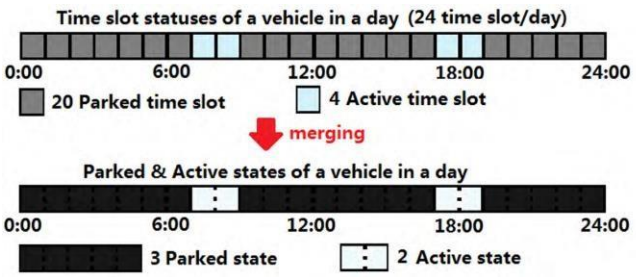


FIGURE 6. Method to obtain the parked states and the active states.

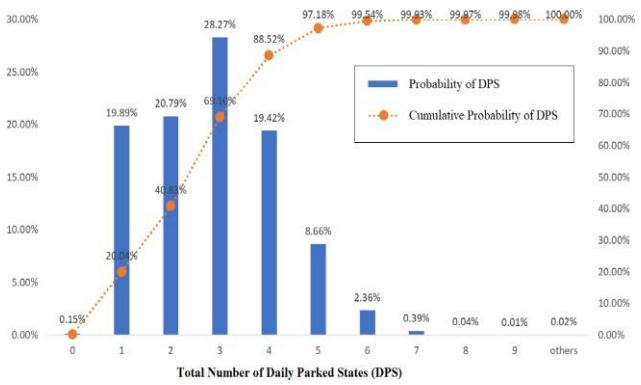


FIGURE 7. Probability distribution of the total number of daily parkedstates.

C. PARKED & ACTIVE STATES

For a privately-owned vehicle, we split each day into some parked states and active states supported the vehicle trips. Hence, by merging the adjacent parked/ active time slots of a day, we obtain the parked and the active states of the vehicle, as shown in Figure.6.

From the info of the 7520 vehicles spanning 61 days, we obtain the probability distribution of the entire number of daily parked states (DPS) as shown in Figure.7. The average total number of daily parked states is 2.85. We know that the All-day parking (none active state, one parked state) ratio is 20%.

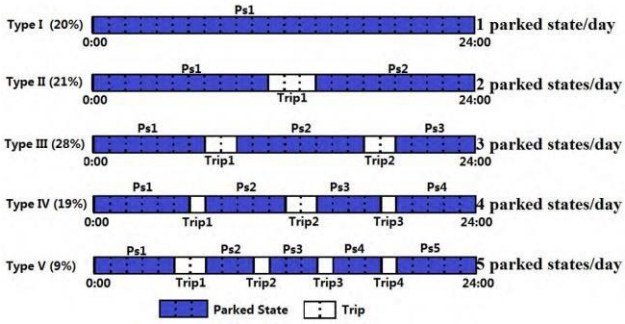


FIGURE 8. The five regular parked patterns accounted for 97%.

Now we know that one to three trips /day ratio is 68.58%; four trips/day ratio only is 9%, and more than four trips/day ratio is less than 3%.

TABLE 2. Statistic analysis result of privately-owned vehicles in Changsha

Statistic Metric	Empirical value	Unit	Description
ADPT	22.63	hour/day	Average daily parked time
ADPRP	14.6	hour/day	Average daily parked time in the place of residence
ADPTS	20.54	state/day	Average total number of parked time slots per day
ADPS	2.85	state/day	Average total number of parked states per day
ADT	1.85	trip/day	Average amounts of daily trips
AAS	0.73	hour/active state	Average trip time
R_DP_0	20	%	All-day parking radio
R_DP_1	21	%	One trip per day radio
R_DP_2	28	%	Two trips per day radio
R_DP_3	19	%	Three trips per day radio
R_DP_4	9	%	Four trips per day radio

The average numbers of daily trips, *ADT*, which denotes the daily vehicular motion frequency, is

$$ADT = \sum_{i=1}^{NumTrip} i \cdot Prob\_Trip_i = 1.85 \qquad (11)$$

Combined with the average privately-owned vehicles daily running time is about 82 min/day, the average time of an active state is 0.73 hours/day

from the data. Table.2 sumarizes the statistical analysis results of real data.

D. URBAN PRIVATELY-OWNED VEHICLE ACTIVITY MODEL

Based on the analysis results of normal parked states of vehicles, we obtain daily parked patterns which account for 97% of the population, as shown in Figure.8.

Combined with the very fact that privately-owned vehicle within the urban environment has one xed place of residence and routinely depart from and return to the place, there are 23 types of daily activity patterns with the parked places, as shown in Figure.9.

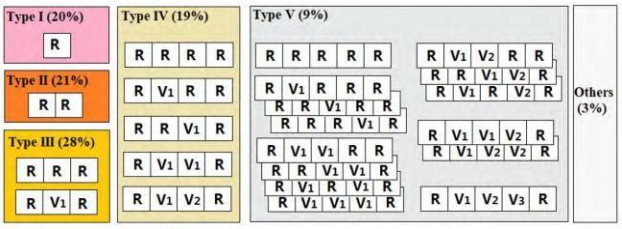


FIGURE 9. The 13 Daily vehicle activity patterns with the parked place.

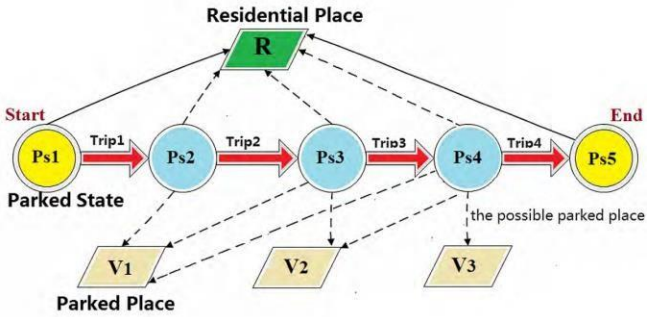


FIGURE 10. Urban privately-owned vehicle activity model.

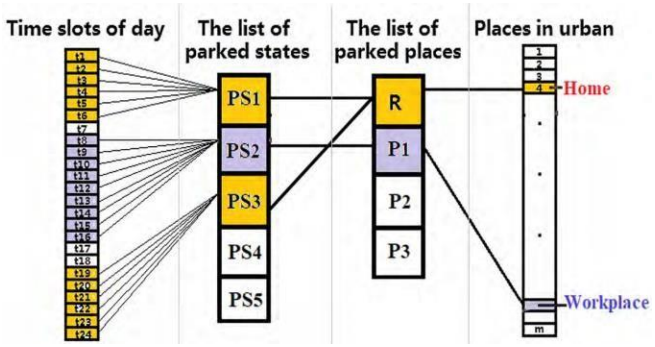
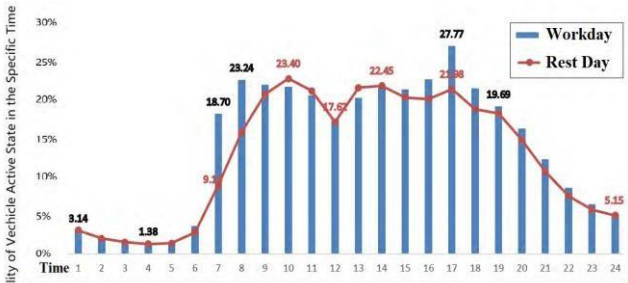


FIGURE 11. The instance of a vehicle's daily activities with the activity model.

From the above daily activity patterns, the probability of that the number of daily parked places is fewer than five accounted for 97%. Therefore, we propose the activity model of privately-owned vehicles for urban vehicle network based on the privately-owned vehicle activity patterns, as shown in Figure.10.

The daily parked behaviors of the vehicle belong to the parked type t4, and its activity model description is shown in Figure11.

Based on the various vehicle activity patterns between the workdays and therefore the rest days, as shown in figure 12, there are two activity models for a vehicle.



Time	1	2	3	4	5	6	7	8	9	10	11	12
Workday	3. 14%	2. 09%	1. 64%	1. 38%	1. 50%	3. 75%	18. 70%	23. 24%	22. 59%	22. 29%	21. 21%	17. 98%
Rest Day	3. 15%	2. 06%	1. 57%	1. 32%	1. 44%	2. 89%	9. 14%	16. 26%	21. 29%	23. 40%	21. 76%	17. 62%
Time	13	14	15	16	17	18	19	20	21	22	23	24
Workday	20. 85%	22. 19%	21. 98%	23. 34%	27. 77%	22. 14%	19. 69%	16. 72%	12. 65%	8. 80%	6. 61%	5. 19%
Rest Day	22. 18%	22. 45%	20. 89%	20. 66%	21. 98%	19. 32%	18. 72%	15. 19%	10. 96%	7. 77%	5. 92%	5. 15%

FIGURE 12. Distributions of daily activities of vehicles in workday & rest day

By embedding the calendar into the vehicle system, the vehicle can distinguish whether the current day is a working day or a rest day. Therefore, the urban vehicles generate the two activity models, depending on their history traces records of the working days and ones of the rest days respectively. Then the vehicles adaptively choose the right model in their daily operations.

V. URBAN VEHICULE NETWORK FRAMEWORK

In this section, we propose our vehicle activity model for the Motivated by the characteristics of privately-owned vehicles in urban environment discussed above, we present a location based urban vehicle network, which we term LUV, for the urban IoT data transmission.

A. LOCATION-BASED MECHANISM

The unique place of residence of a vehicle implies that it can address the vehicle node within the vehicle network. When the vehicle network needs to transfer IoT data to a specied location, it can easily find the target carrier by comparing the place of residence of the candidate vehicle and therefore the data destination.

Hence, the Location-based mechanism offers the possibility for the urban vehicle network to accommodate millions of self-originating vehicle nodes in the sophisticated city environment.

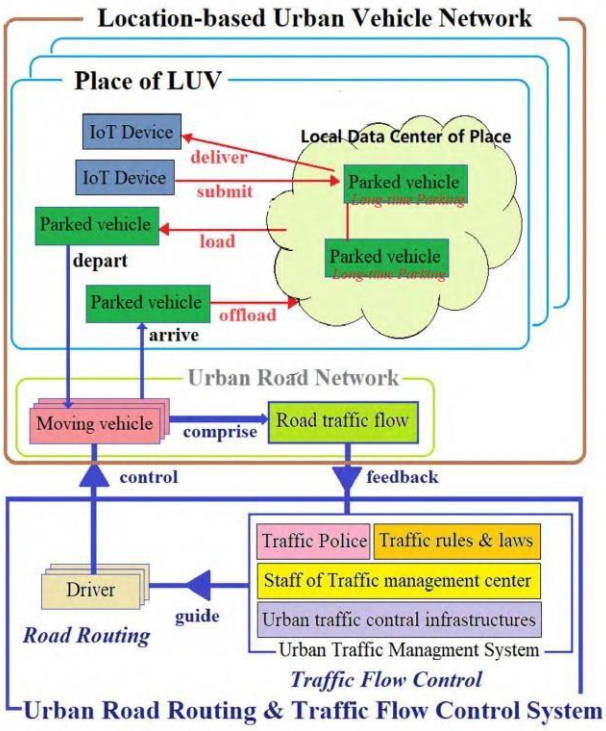


FIGURE 13. Network framework of LUV.

B. NETWORK FRAMEWORK

By following the existed people/cargo transmission pattern of vehicles, LUV is parasitic on the existed urban vehicle transportation network to obtain the mega-size network trafic control and path routing in the complex urban environment.

The primary network operations are composed of three components: message exchange at a place between IoT devices and therefore the local data center which is deployed on the parking vehicles, message routing (relay-place) at an area by the local data center, and message forwarding from place to place by the moving vehicles.

C. LOCAL DATA CENTER OF PLACE

Based on our previous analysis of the data traces, we that almost one-fifth of private vehicles are in the state of all-day parked and more vehicles are in the states with long-time parking. It shows the practicability of deploying the distributed local data center of place on the all-day parked vehicles and therefore the long-time parked vehicles within the area.

To describe the deployment scheme of place data center, we introduce two types of nodes in place as follows.

Local node: a parked node at its place of the parked list of its activity model.

Foreign node: a parked node not in its place of the parked list of its activity model.

We devise the subsequent approach for deployment of the local data center among the local nodes in steps.

A: OBTAINING THE DEMANDS OF THE DATA CENTER IN THE PLACE

By the registration information from the IoT devices deployed in the place, LUV can obtain the IoT data cache demands of the area for the local data center. Depending on the data needs of the IoT devices and the IoT data cache capacity of a vehicle node, the number of required vehicle nodes in the local data center can be obtained.

B: CHOOSING DATA CENTER NODES

The probability of remaining in parked states (Prob_RPS) during a time slot can be inferred from the local node's activity model which is generated and updated by its history trace records. We merely randomly choose these local nodes as data centers when their Prob_RPS satisfy the predened threshold Thr_RPS, till the amount of data center nodes fulll the demands. For there are plenty of all-day parked vehicles and long-time parked vehicles in reality.

C: RETIRING DATA CENTER NODES

Prob_RPS of a vehicle node varies with me. As a part of the local data center, when its Prob_RPS is lower than the predened threshold Thr_RPS, the data center node stops caching IoT data and sends saved cache data to other data center nodes. Then

the node into a carrier mode and cargo the IoT data from the local data center, and carry the IoT data to the destination place with its trip.

D: PLACE OF LUV

LUV obtains places from the urban street blocks. Street blocks, because the results of the continued urban planning process, is the fundamental units of the urban trafic network. Generally, the urban trafic network is designed and operated to meet the trafic demands of every street block in the city. Since LUV has an equivalent transmission pattern with the urban trafic network, the places of LUV come from the urban street blocks in reality when the digital map of the city identify its boundaries.

Based on its historical traces, each vehicle can determine its place of residence and therefore the daily visiting place list. According to the activity model of a vehicle, the places where the 2 parked states belong to compose a place-place pair. After all parked vehicles in the same area share their place-place pairs in the local data center, the local data center obtains the vehicle table and the place routing table. Moreover, according to the vehicles owners' will, the parking time in each parked place from the activity model can be shared with the local
data center.

E: IoT DATA SUBMISSION & DELIVERY

In a place of LUV, the IoT devices exchange data with the local data center by building the wireless reference to the nearby local nodes. The local data center delivers the IoT data to the vehicles which are ready to leave, and receive the local data from the vehicles arrived, as shown in gure.14.

The wireless connection range of the vehicle is longer than the one of the IoT devices. Although the communication between the vehicle and the IoT device is limited by the communication range of the IoT devices, the space of the V2V communication can reach farther. Such an extended communication range make it easy for building the vehicle-based local data center to cover the entire area.

The local data center connects the other local nodes and the foreign nodes within the area for data delivery and submission.

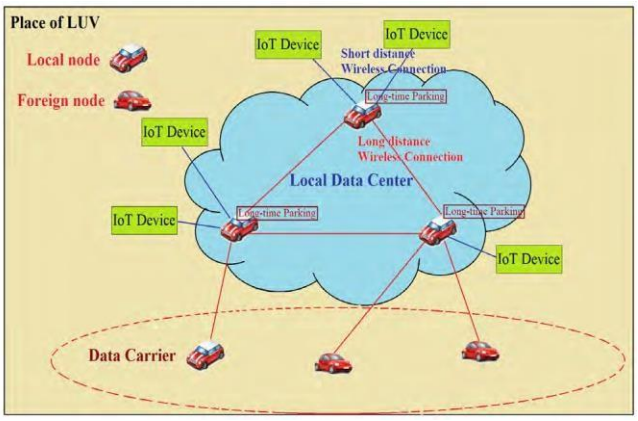


FIGURE 14. The wireless connections of IoT-vehicle and V-V in the LUVplace.

F: ENERGY CONSUMPTIONS

Nowadays, most of the vehicles have not to be equipped with high-power batteries yet. The vehicular terminals have to be turned off after the vehicles stop. However, according to the electrication trend of the automotive industry, it can be expected that the next generation of vehicles will have the ability to power vehicle-mounted terminals around the clock. Therefore, during its parking, by peer to peer wireless connections, the vehicles can collect data from the IoT devices, submit data to the servers, and interact with the opposite parked vehicles. Although the energy scarcity of the IoT devices and sensors limits their wireless communication range, the high density of parked vehicles within the populated area ensures that the IoT devices can be connected to the nearby vehicles within their short wireless communication range.

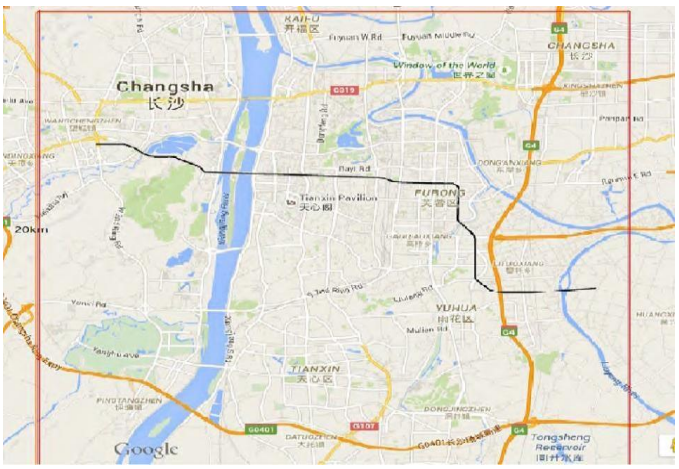


FIGURE 15. Targeted LUV area in Changsha, China.

G: INCENTIVES FOR CAR OWNERS

Given the very fact that the car owners buy the facility spending of the vehicular terminals or other indirect costs, the incentives for them to participate in the urban vehicular network is necessary.

Considering that urban vehicular networks for collecting public IOT data are non-prot networks served smart cities, municipalities should provide public resources for the incentives. The system records the total amount of historical IOT data transmitted by each vehicle. Similar to airline mileage conversion points, assign points to the vehicles consistent with their total amounts of data transmission. When the vehicles have earned enough points, they gain priority access to specific public resources in the city by redeeming their points. For instance, the car owners can obtain one-time free parking in a particular area with its points. In the case, it sounds be attractive to car owners thanks to the shortage of parking resources in modern cities.

VI. NETWORK EVALUATION

In this section, the set of real-life data on privately-owned vehicles is utilized for the network evaluation. To reduce the amount of calculation, we set the urban area scope of Changsha from N28.07 to N28.27, E112.90 to E113.10, which is shown in Figure 15.

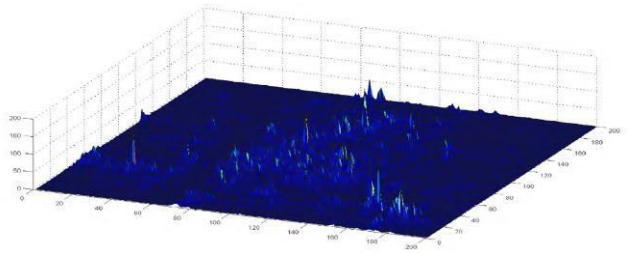


FIGURE 16. LUV place distribution with Thr_density 0 (Changsha,China).

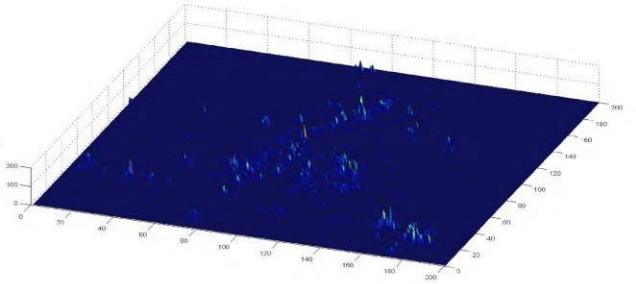


FIGURE 17. LUV place distribution with Thr_density 19 (Changsha,China).

A. PLACE IDENTIFICATION IN LUV

Based on our approach for place identication in LUV [25], we rest divide the area, as shown in Figure.16, which is 20km by 20km into 40,000 units, each with a neighborhood of 100m by 100m. The entire duration of the vehicle in each unit is accumulated over the entire observing period and stored in a matrix, MS. The row of the matrix MS is vehicle ID, and column is unit ID. The total number of vehicles which belongs to the area is 5190. As the number of units is 40000, the size of matrix MS is 5190 by 40000. A vehicle's total residence time in each unit is stored within the elements of the matrix. If we merely set the Thr_time to 1, the matrix becomes sparse, and the non-null rate is about 0.43% (89870 non-empty elements). If we set Thr_density to 19, we identify 873 LUV places which account for 2.18% of the total area. Figure.16 is the intermediate result where parameter Thr_density has not been applied yet. Figure.17 illustrates the distribution of the 873 LUV places. LUV allows messages exchange within places to ensure relative stable and reliable connection among vehicles.

	177	239	223	403
269	358	531	339	
	275	691	330	
		488		
		203		

FIGURE 18. LUV places(4km*4km) and the local vehicles

Place:	1	2	3	4	5	6	7	8	9	10	11	12	13
1		6	1	2	3	5	4	2	1	2	0	3	0
2	8		8	5	0	8	10	3	2	3	2	2	0
3	1	7		8	1	3	7	6	2	5	2	3	0
4	3	8	20		3	7	7	4	2	2	5	6	2
5	4	1	3	2		14	5	0	3	8	0	2	0
6	13	9	3	5	7		18	2	9	9	3	6	2
7	10	19	14	6	7	28		35	5	21	12	9	4
8	3	5	9	5	0	3	16		3	7	14	4	1
9	2	1	4	2	3	14	2	3		18	2	9	4
10	6	7	10	7	6	16	26	10	23		41	31	5
11	1	2	3	4	1	1	8	9	3	24		8	1
12	5	5	6	3	6	7	13	6	11	16	12		17
13	1	0	0	1	2	1	2	0	2	8	1	11	

FIGURE 19. Data links of LUV places.

At the same time, the places where the vehicles will visit next provide a likely route for message delivery. By using simple threshold methods, we can identify concentrated vehicle places in an urban area that can effectively serve as places in LUV. Given the multiple tunable parameters, the method can effectively control the size of the place, the number of vehicles, and the required frequency or residence time in a place.

B. DATA LINKS OF PLACES IN LUV

Considering the vehicle nodes which from real data set is much less than the real quantity of vehicles in Changsha, China, we zoom in the place area to acquire enough local Nodes in one place to review the connectivity of places in LUV over the real-life data. We divide the area into 25 units, each with an area of 4km by 4km. By our threshold-based approach for identifying the places, The result as below:

The residential place and the visited place of one vehicle build a data link between the two places. Therefore, we obtain the data links between these places as shown in gure.19.

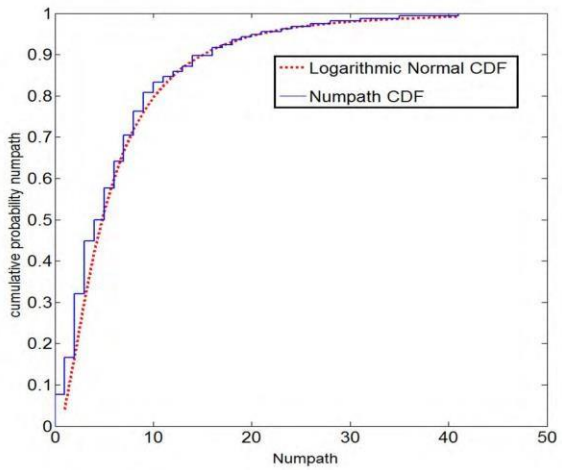


FIGURE 20. The total number of data links between places CDF.

The total number of data links between places ts logarithmic normal distribution, as shown in Figure.20.

The connectivity rate in LUV is 96.15%. It indicates that urban vehicles can provide data service between places and the network performance depends on the amounts of vehicle nodes. LUV will improve as well. Therefore, within LUV, the millions of urban vehicles can provide low-cost local data access services to hundreds of millions of IoT devices in the city.

VII. CONCLUSION

With the rapid development of Smart City related technologies like IoT, big data, and wireless communication, the demands for the IOT data in smart cities have snowballed. In addition to the 5G network, smart cities can also deploy the vehicle-based DTN network as the non-real-time IoT data transmission platform to reinforce the IoT data collection capability and reducing the IoT data collection costs in smart cities.

According to the essential features of urban vehicles from the analysis of the trace data of the private cars, we propose a location-based urban vehicle network (LUV) for IoT data transmission in the urban environment. In LUV, the parked vehicles, the daily activity patterns of vehicles and the existing urban vehicular transportation network are fully utilized to reduce the network complexity and improve the network scalability for practical application.

Due to prohibitive costs and policy constraints, it is challenging to deploy sufficient sensors in the urban environment for acquiring public sensing data. Compared to sensor deployment, collecting sensing data generated by these sensors distributed in urban is even harder. Though message exchange only happens between parked vehicles within places, private vehicles can perform various other tasks like sensing urban environment from multi-sensor mounted on vehicle or gathering sensing data from the roadside sensors when moving. Relying on LUV, the urban sensing servers deployed especially places can collect these sensing data on vehicles.

The works of this paper are based on our previous work over the last four years [24][26]. There are still many aspects for us to study in the future. For the parking places make a profound impact on vehicles, the type of place, the spatial scale of places, and the vehicle capacity of parking place, is yet to come. Supported the place studies, we will utilize the features of places to design the details of LUV further. Furthermore, in this paper, there are two activity models of vehicles that are divided merely by workday and day of rest which vehicles detect by themselves. In the further work, the activity model of vehicle can be refined to improve the accuracy of predicting the current behaviour of the vehicle.

REFERENCES

[1] H. Schaffers, N. Komninos, M. Pallot, B. Trousse, M. Nilsson, and A. Oliveira, "Smart cities and therefore the future Internet: Towards cooperation frameworks for open innovation," in The Future Internet Assembly (Lecture Notes in Computer Science), vol. 6656. Berlin, Germany: Springer-Verlag, 2011, pp. 431446.

[2] A. Zanella, N. Bui, A. Castellani, L. Vangelista, and M. Zorzi, "Internet of Things for smart cities," IEEE Internet Things J., vol. 1, no. 1, pp. 2232, Feb. 2014.

[3] R. Zhu, M. Ma, L. Liu, and S. Mao, "A special section in IEEE Access: Cooperative and intelligent sensing," IEEE Access, vol. 5, no. 1, pp. 2782427826, 2017.

[4] D. Puthal, S. Nepal, R. Ranjan, and J. Chen, "Threats to networking cloud and edge datacenters in the Internet of Things," IEEE Cloud Comput., vol. 3, no. 3, pp. 6471, May/Jun. 2016.

[5] M. Agiwal, A. Roy, and N. Saxena, "Next generation 5G wireless networks: A comprehensive survey," E Commun. Surveys Tuts, vol. 18, no. 3, pp. 16171655, 3rd Quart, 2016.

[6] G. Wunder, P. Jung, M. Kasparick, T. Wild, F. Schaich, Y. Chen, S. Ten Brink, I. Gaspar, N. Michailow, A. Festag, and L. Mendes, "5GNOW: Non-orthogonal, asynchronous wave-forms for future mobile applications," IEEE Commun. Mag., vol. 52, no. 2, pp. 97105, 2014.

[7] M. Strohbach, H. Ziekow, V. Gazis, and N. Akiva, "Towards a big data analytics framework for IoT and smart city applications," in Modeling and Processing for Next-Generation Big-Data Technologies. Berlin, Germany: Springer, 2015, pp. 257282.

[8] A. Galati, Delay Tolerant Network. Saarbrucken, Germany: Lambert Academic, 2010, pp. 215.

[9] S. Mumtaz, L.-L. Yang, C. Wang, F. Adachi, and N. Ali, "Smart-device-to-smart-device communications: Part 2," IEEE Commun. Mag., vol. 52, no. 4, pp. 1819, Jun. 2014.

[10] X. Hou, Y. Li, M. Chen, D. Wu, D. Jin, and S. Chen, "Vehicular fog computing: A viewpoint of vehicles because the infrastructures," IEEE Trans. Veh. Technol., vol. 65, no. 6, pp. 38603873, Jun. 2016.

[11] M. Gerla and L. Kleinrock, "Vehicular networks and the future of the mobile Internet," Comput. Netw. J., vol. 55, no. 2, pp. 457469, 2011.

[12] P. Hui, J. Crowcroft, and E. Yoneki, "BUBBLE rap: Social-based forwarding in delay-tolerant networks," IEEE Trans. Mobile Comput., vol. 10, no. 11, pp. 15761589, Nov. 2011.

[13] Y. Mao, "PASA: Passive broadcast for smartphone ad-hoc networks," in Proc. IEEE 23rd Int. Conf. Comput. Commun. Netw., Shanghai, China, Aug. 2014, pp. 18.

[14] C. Liu, C. Chigan, and C. Gao, "Compressive sensing based data collection in VANETs," in Proc. IEEE WCNC, Shanghai, China, Apr. 2013, pp. 17561761.

[15] G. Grassi, D. Pesavento, G. Pau, R. Vuyyuru, R.Wakikawa, and L. Zhang, "VANET via named data networking," in Proc. INFOCOM WKSHPS,Toronto, ON, Canada, Apr./May 2014, pp. 410415.