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Destination Prediction-Based Scheduling Algorithms for Message Delivery in IoVs

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ABSTRACT Destination related applications are playing an important role in Internet of Vehicles(IoVs), which can provide people with convenience or business profit, such as traffic jam warning or parking guide. However, in reality, people hesitate to share their destination information to other people due to operation inconvenience, which requires service providers to predict vehicles' destinations in advance in order to deliver them destination related messages. Some papers have considered the delivery scheduling problem of destination related information. But, they neglect the destination prediction problem with the assumption that vehicle's destinations are known in advance. In this paper, we target the delivery scheduling problem of destination related information in the case of destinations unknown to others in IoVs. First, a realtime destination prediction framework with machine learning models is proposed, with which a vehicle's destination can be predicted while traveling. Then, we propose a delivery profit maximization algorithm for service providers to select a proper location to deliver destination related information to each vehicle. Simulations with real vehicle trajectories show that our scheduling algorithm performs well and can successfully select a proper location to disseminate destination related information.

INDEX TERMS Internet of Vehicles, destination related information, destination prediction, accuracy profit, forwarding profit.

I. INTRODUCTION

Internet of Vehicles is composed of a collection of vehicles equipped with On Board Units (OBUs) and Road Side Units (RSUs) connected to the centralized network, shown as Fig. 1. Each vehicle can communicate with each other in an ad-hoc network pattern or with RSUs in a centralized pattern by wireless technology, such as WAVE and LTE-V [1]. The centralized pattern of communication is commonly referred as Vehicle to Infrastructure(V2I), and the ad-hoc network is referred as Vehicle to Vehicle(V2V). In IoVs, RSUs play an important role, which not only extend the service range of IoVs, but also provide high speed message forwarding service for vehicles with their high bandwidth links to the center service providers [2]. Usually, messages delivered in the network are generated from the center service providers and then sent to vehicles with RSUs. Once a message is accepted by a vehicle, it can also be forwarded among vehicles.

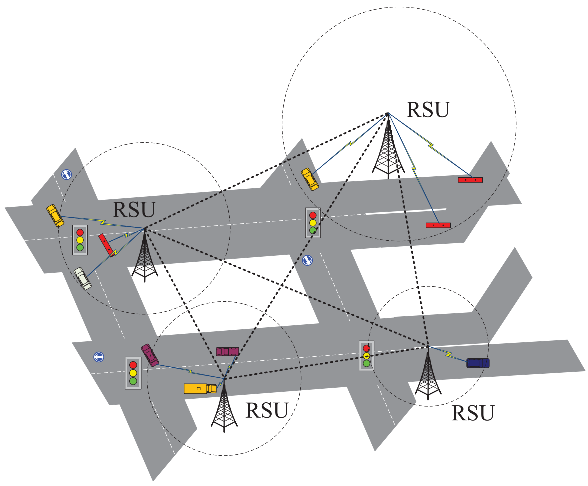

FIGURE 1. Architecture of IoVs.

Based on this process, the service providers can provide many services to users, such as ads delivery and entertainment service. Some of them are location related, especially destination related, which need vehicle nodes to share their

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destinations of current trips in order to get better services. However, this requirement cannot always be satisfied due to the privacy problem or operation inconvenience. Commonly, only current location information can usually be shared. As service providers, how to utilize these information to provide the destination related services to vehicles is an important problem to be solved.

In this paper, we consider the scenario of the destination related information delivery services. In this scenario, service providers would like to send each vehicle its destination related information, such as traffic jam, parking slot or ads information. However, vehicles don't provide their destinations actively, and they only provide their current locations to the service providers, due to privacy problem [3]–[5]. Therefore, the service providers should determine what destination related information to send to each vehicle and when to send. Intuitively, the service providers first determine what the destination of each vehicle is based on each vehicle's current trajectory in order to prepare its destination related service information. Then the service providers should figure out when or where to send the information to the vehicle.

For the first problem, several typical works have been done with different approaches. Some of the approaches are based on the Markov model [6]. And deep neural networks(DNNs) are also used in some approaches [7]. For the second problem, there are some works too. Some balance algorithms are proposed to balance the message delivery process and the communication cost, such as [8], [9]. However, our paper considers the two problems together, and solves the problem with a new method. There are some challenges to solve the problem. First, the prediction should be as accurate as possible in order to be able to find a proper location to deliver messages. Second, fewer messages should be sent to save the RSU bandwidth. Third, messages should be sent early to be forwarded to more neighbors.

In this paper, we first propose a realtime destination prediction algorithm based on machine learning models. With history trajectories as training data, the destination prediction algorithm can obtain a prediction model to predict the destination of current trip. When a vehicle is traveling to its destination, its destination can be predicted by the service provider with its current trajectory in real time. Once the destination is predicted, the service provider should choose a proper time or location to send the destination related information. Then the conceptions of accuracy profit and forwarding profit are proposed, which are used to evaluate the profit of message delivery. Then two algorithms are proposed, whose purpose is to find a time slot or location to optimize the accuracy profit and the forwarding profit. Simulations with real vehicle trajectories show that our scheduling algorithm performs well and can successfully select a proper location to disseminate destination related information.

The main contributions of this paper are listed as follows:

1) We propose a realtime destination prediction algorithm, which can predict a vehicle's destination while traveling.
2) Two evaluation factors – accuracy profit and forwarding profit are proposed to evaluate the proposed algorithms.
3) Then the Delivery Profit Maximization Algorithm and Communication Scheduling Algorithm are designed to select a proper time slot or location to deliver the destination related information, with the accuracy profit and the forwarding profit optimized.
4) An extensive simulation is conducted to evaluate the algorithms and the results show that they perform better than current algorithms.

The rest of this paper is organized as follows. Section II discusses some related work. The system model and problem formulations are given in Section III. Section IV describes the details of the protocol we propose. Then all the simulation results are described in section V. Finally, the paper and future work is concluded in section VI.

II. RELATED WORK

This paper focuses on two aspects, including destination prediction and RSU scheduling problems in IoVs. Therefore, we will summarize related works through the above two aspects.

A. DESTINATION PREDICTION

Referring to the destination prediction, there are mainly two classes of related works.

The first is to extend the trajectory data set to solve the trajectory sparsity problem. Paper [10]–[13] have given solutions about this problem. Moving vehicles' trajectories can be viewed as a set of measurements which can be modeled as a collection of sparse time series. A spatio-temporal hidden Markov model is proposed in [13] to model correlations among different traffic time series, which can learn parameters while contending with the time series' sparsity. A named Sub-Trajectory Synthesis(SubSyn) is proposed in [10] to address the data sparsity problem. SubSyn first decomposes historical trajectories into sub-trajectories comprised of two adjacent locations, which are connected to ''synthesised'' trajectories. This process expands the historical trajectory dataset to contain much more trajectories.

The second class is the trajectory prediction model construction problem. Most of traditional methods of destination prediction are based on the Markov chain models or clustering model. However, with this kind of model, the geographical distribution and the time property of the trajectories are neglected. Paper [14] proposes a density-based clustering function to predict the final destination of trips with several starting locations of trajectories. Paper [6] proposes a destination prediction algorithm, which trains the semantic transfer probability models in advance. But the solution may not work well when it meets a new area, as its semantic information is not known in advance. In addition, these approaches utilize physics-based motion models such as kinematic and dynamic models, which are fit for the short term prediction other than the long-term prediction.

Currently, neural network based prediction mechanisms are also proposed, which are more fit for long term predictions. Paper [7] employs a deep neural network(DNN) for trajectory prediction and the time cost of training is very short. But, DNN has the problem of gradient explosion or disappearance while training network model which should be improved. An efficient vehicle trajectory prediction framework based on recurrent neural network(RNN) is proposed in [15]. The prediction of vehicle trajectory involves all aspects of the road environment, such as the shape and location of roads. They solve this problem through employing the recurrent neural network called long short term memory (LSTM) based on the massive amount of trajectory data.

B. RSU SCHEDULING

RSUs play an important role on message delivery in IoVs, and there are mainly two classes of researches on this area.

First, how to deploy RSUs in IoVs is a critical problem, due to the high cost of RSU infrastructures [16], [17]. Some works have been done on this problem in order to minimize deployment cost such as [18]–[20]. In [18], given a region and a delay bound, the authors find the optimal placement between cable-connected RSUs(c-RSUs) and wireless RSUs(w-RSUs), and a greedy-based algorithm is proposed in order to accomplish it. In addition, the delay-bounded and cost-limited RSU deployment problem in urban VANETs is studied in [20]. The problem is proved to be NP-hard and then a greedy-based individual reparation algorithm is proposed.

Second, there are also several works on RSU scheduling [21]–[24]. These works mainly get a collaborative strategy of multi-RSUs to make the whole system optimal. Compared with [21], [23] proposes a framework considering low cost dissemination of events. Each RSU can disseminate only a finite number of events at a certain time and has a cost associated with each RSU. Two optimization algorithms are proposed so as to maximize the number of subscriptions matched. Besides, some works solve the communication scheduling problem, such as [24]. Paper [24] presents an analytical model for evaluating the performance of several distributed beaconless dissemination protocols in linear VANETs (e.g., highways), which can avoid broadcasting storm. Our paper focus on the RSU scheduling problem of information delivery in order to select a proper time slot to disseminate information.

III. SYSTEM MODEL

A. BASIC FRAMEWORK

We consider an internet of vehicles $G(R, V, E)$. In the network G, K RSUs are deployed, denoted as $R = \{r_1, r_2, r_3, \ldots, r_K\}$. Each RSU can communicate with several vehicles in its coverage range at the same time, by LTE-V or WAVE technologies. But a vehicle can only be covered by one RSU at any time. We assume that all the RSUs are evenly distributed like grids and in each grid there is an RSU covering the grid area. Thus, when a vehicle passes by an RSU, it will connect to a new RSU as soon as it disconnects from the last RSU. For the RSUs, there is a parameter called bandwidth, denoted as $W = \{w_{r_1}, w_{r_2}, w_{r_3}, \ldots, w_{r_K}\}$. In this formula, $w_{r_k}(r_k \in R)$ means that RSU r_k can simultaneously send messages to vehicles with at most w_{r_k} bandwidth.

There are N vehicles (also called nodes) denoted as $V = \{v_1, v_2, v_3, \ldots, v_N\}$ in the network. Each vehicle $v_n(v_n \in V)$ travels in the network and forms a spatiotemporal sequence, namely trajectory, denoted as $L_n = (l_n^{t_1}, l_n^{t_2}, l_n^{t_3}, \ldots, l_n^{t_m})$. L_n is the trajectory of vehicle v_n and $l_n^{t_m}$ is the location of v_n at time t_m. All the vehicle trajectories constitute the trajectory set, denoted as $L = \{L_1, L_2, L_3, \ldots, L_N\}$. As each location in a trajectory is covered only by one RSU, the vehicle trajectory L_n can also be described with RSU sequences, such as $L_n = (r_x, r_y, r_z, \ldots)$. That means $l_n^{t_1}$ is in the communication range of RSU r_x. Besides, the time period T can be divided to a lot of time units (also called time slots) of the same length Δt, such as a minute or half a minute. Then L_n can be denoted as $(r_{v_n}^{\Delta t_1}, r_{v_n}^{\Delta t_2}, r_{v_n}^{\Delta t_3}, \ldots r_{v_n}^{\Delta t_m})$. $r_{v_n}^{\Delta t_m}$ means at the m-th slot, vehicle v_n is covered by r. Each vehicle can communicate with RSUs and the bandwidth cost of the communication is C_{v_n}, which means the message delivery cost for v_n on bandwidth.

Each vehicle can contact with the other vehicles when they locate in each other's communication range and their communications are denoted as $E = \{e_{v_1,v_2}^{t_1}, e_{v_1,v_2}^{t_2}, e_{v_1,v_2}^{t_m}, \ldots, e_{v_n,v_{n'}}^{t_m}\}$. $e_{v_n,v_{n'}}^{t_m}$ means vehicle v_n and $v_{n'}$ can communicate at time t_m. In this paper, we assume that all the vehicles covered by the same RSU are neighbors and each of them can communicate with the others.

According to the system basic framework, the vehicle trajectory model can be described as Fig. 2. The transverse axis is the time axis standing for the sequence number of time unit and the longitudinal axis is the vehicle number. Each row is a trajectory of a vehicle. Take the first row as an example. The starting point of vehicle v_1 is r_1 at time slot Δt_1, the destination is r_4 at time slot Δt_4 and at time slot Δt_2 it is covered by r_2. Take the first column as an example. At time slot Δt_1,all the vehicles covered by RSU r_1 can communicate with r_1 with at most bandwidth w_{r_1}.

B. PROBLEM FORMULATION

In this paper, we focus on the information dissemination problem in IoVs. We consider the following scenario.

(1) All the RSUs in the network are connected and they are controlled by the service providers.

(2) Every vehicle in the network is traveling to a designated destination, which is known only by itself and the service providers don't know about it.

(3) In the destination area of every vehicle, there is some information about this area to be delivered to the vehicle, such as parking information and ads information. The service providers want to send these information to the vehicles in

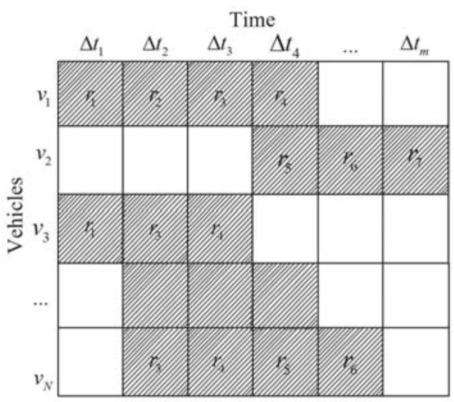

FIGURE 2. Vehicle trajectory model.

advance for two purposes. First, these information can help the vehicle make decisions before its arriving, such as parking advice or traffic jam warning. Second, these information can be forwarded to other vehicles that have the same destination.

(4) All the destination related information must be sent out from the RSUs first and then forwarded among vehicles. In addition, these information should be delivered to related vehicles as early as they travel to their destinations.

(5) In order to avoid the broadcast storm problem and save the bandwidth resource, the RSUs cannot send vehicles their destination related information frequently. Thus, during a vehicle's traveling from the starting location to the destination, only a closed RSU can be chosen to send its destination related information to the vehicle once.

(6) Some of vehicles don't want to actively share their exact realtime locations to others. However, they need to connect to an RSU to have communications with the internet, which will expose their rough locations to the service providers. Therefore, it is considered that the service providers know by which RSU each vehicle is covered most of the time.

Based on the above descriptions, the service providers' purpose is to send destination related information to each vehicle and then through the vehicle to forward it to other vehicles. To achieve that, the service providers need to predict each vehicle's destination at first and then select a proper location(RSU) to disseminate the destination related information. In different time slots, the destinations predicted are varying with the vehicle's traveling stage. With the prediction accuracy varying, the probability of vehicle receiving correct information changes too. So we define the accuracy profit AP_{v_n}, which is related to the information delivery accuracy on vehicle v_n. Once a vehicle receives the destination related information, it can also forward it to other neighbor vehicles. If the number of neighbor vehicles is large, the vehicle can forward the information to more neighbors. Here, we define another profit – forwarding profit FP_{v_n}, which is related to the number of vehicle v_n's neighbors.

Therefore, we define the following two kinds of objectives.

First, when the service providers send vehicles their destination related information, the first objective is to maximize the total accuracy profit AP_{total} and the average accuracy profit AP_{avg} of each message sent by the service providers. This is formally specified as follows:

For the vehicle set V, choose a proper slot for each vehicle, namely $S = \{s_{v_1}, s_{v_2}, s_{v_3}, \ldots, s_{v_N}\}$, to achieve:

$$\max AP_{total} = \sum_{s_{v_n} \in S} AP_{v_n} \tag{1}$$

$$\max AP_{avg} = \frac{\sum_{s_{v_n} \in S} AP_{v_n}}{\sum_{s_{v_n} \in S} C_{v_n}} \tag{2}$$

Second, when the forwarding profit is considered, another objective of this problem is to choose a proper slot for each vehicle to maximize the total forwarding profit FP_{total} and the average forwarding profit for each vehicle FP_{avg}. This is formally specified as follows:

$$\max FP_{total} = \sum_{s_{v_n} \in S} FP_{v_n} \tag{3}$$

$$\max FP_{avg} = = \frac{\sum_{s_{v_n} \in S} FP_{v_n}}{\sum_{s_{v_n} \in S} C_{v_n}} \tag{4}$$

The two kinds of objectives are subjected to the following conditions.

$$s_{v_i} = \begin{cases} 0 \\ r_{v_i}^{\Delta t_x}, \quad r_{v_i}^{\Delta t_x} \in L_i \end{cases} \tag{5}$$

$$AP_{v_n} \in [0, 1], \quad \forall v_n \in V \tag{6}$$

$$FP_{v_n} \in [1, +\infty), \quad \forall v_n \in V \tag{7}$$

$$\sum_{v_i \in V \text{ and } r_{v_i}^{\Delta t_x} = r_j} C_{v_i} <= w_{r_j}, \forall r_j \in R, \quad \forall \Delta t_x \in T \tag{8}$$

In objectives (2) and (4), $\sum C_{v_n}$ means the total bandwidth cost of message delivery. (In this paper, we define the bandwidth cost for each message delivery is the same and the value is 1.)

Constraint (5) specifies that each vehicle can only be sent no more than a piece of message during its trip. When $s_{v_i} = 0$, vehicle v_i is not sent any message. Otherwise, it is sent a message at location $r_{v_i}^{\Delta t_x}$.

Constraint (6) specifies that the value of accuracy profit is between 0 and 1 and is related to the accuracy of information delivery.

In formula (7) means the value of forwarding profit should be at least 1, which means at least one vehicle has received the message.

Constraint (8) means that at any slot Δt_x, the bandwidth cost for RSU r_j sending messages to vehicles simultaneously is no more than the RSU's bandwidth w_{r_j}.

C. MAIN IDEA

We focus on the scheduling problem of message delivery on RSUs. Given an internet of vehicles $G(R, V, E)$, our main purpose is to schedule each RSU to send destination related messages to vehicles in its coverage to maximize the above matrics. Thus, the first effort is to predict each vehicle's destination. An accurate prediction may lead an RSU to send a vehicle its destination related message correctly. In Section IV-A, we provide a means to predict a vehicle's destination based on all the vehicles' history trajectories. Once the destination is predicted, the service provider should choose a proper time or location to send the destination related information, described in section IV-B. Then the conceptions of accuracy profit and forwarding profit are proposed in section IV-B.1, which are used to evaluate the profit of message delivery. At last, two algorithms are proposed in section IV-B.3, whose purposes are to find a time slot or location to optimize the accuracy profit and the forwarding profit.

IV. PROTOCOL DETAILS

A. DESTINATION PREDICTION ALGORITHM

In order to schedule the message delivering process on RSUs more properly, we need to predict the vehicle movement status. Thus, in this subsection, we focus on the destination prediction problem in IoVs. Our purpose is to predict each vehicle's destination as accurate as possible. However, the only resources that we can utilize are the history trajectories of each vehicle. Based on these trajectories, we use some machine learning algorithms such as Bayes [25] or LSTM [26] to achieve our purpose.

1) TRAJECTORY PRE-PROCESSING

As formulated in section III-A, any trajectory L_n can be denoted as $(r_{v_n}^{\Delta t_1}, r_{v_n}^{\Delta t_2}, r_{v_n}^{\Delta t_3}, \dots r_{v_n}^{\Delta t_m})$, which is a sequence of several RSUs. But there is a problem in the trajectory data that prevents to use machine learning algorithms directly.

Due to the traffic jam or other factors, a vehicle may stay in the same RSU for a long time. Therefore, many locations in a trajectory may be duplicate, which makes no sense for destination prediction. To solve this problem, when there are consecutive duplicate items in a trajectory, we cut the duplicate ones and only keep one left. As shown in formula (9), if $r_{v_n}^{\Delta t_1} = r_{v_n}^{\Delta t_2} = r_{v_n}^{\Delta t_3} \neq r_{v_n}^{\Delta t_4}$, then L_n should be reformatted to formula (10).

$$L_n = (r_{v_n}^{\Delta t_1}, r_{v_n}^{\Delta t_2}, r_{v_n}^{\Delta t_3}, r_{v_n}^{\Delta t_4}, \dots r_{v_n}^{\Delta t_m}) \tag{9}$$

$$L_n = (r_{v_n}^{\Delta t_1}, r_{v_n}^{\Delta t_4}, \dots r_{v_n}^{\Delta t_m}) \tag{10}$$

2) DESTINATION PREDICTION ALGORITHM

The purpose of destination prediction is that while a vehicle is moving on the way to its destination, the RSUs can predict its destination before its arriving based on its trace. However, the length of the trace changes with the vehicle traveling, and how to train the model and complete the prediction based on the movement stage is the main problem. Thus, we propose a realtime destination prediction algorithm to solve the problem.

The basic idea of algorithm 1 and algorithm 2 is sketched as follows. The inputs of the algorithm are the dataset of all the traces and the current trace of vehicle v_x whose destination is to be predicted. The output is the predicted destination

Algorithm 1 Destination Prediction Algorithm: Training Part

Input:
$L = \{L_1, L_2, L_3, \dots, L_N\}$
$L_n = (r_{v_n}^{\Delta t_1}, r_{v_n}^{\Delta t_2}, r_{v_n}^{\Delta t_3}, \dots r_{v_n}^{\Delta t_m}), L_n \in L$
Output:
M: Model Set for Destination Prediction

1: **function** Training(L)
2: $M = \emptyset$
3: **for** $i \leftarrow 1$ *to* m **do**
4: $TrainingSet_i \leftarrow Select(L, i, Destination)$
5: ▷ Select the first i locations and the
6: destination of each trace in L.
7: $Model_i \leftarrow TrainFunction(TrainingSet_i)$
8: ▷ Do training work on $TrainingSet_i$ with
9: a training function to get a prediction
10: model.
11: $M \leftarrow M \cup \{Model_i\}$
12: **end for**
13: **return** M
14: **end function**

Algorithm 2 Destination Prediction Algorithm: Prediction Part

Input:
$L_x = (r_{v_x}^{\Delta t_1}, r_{v_x}^{\Delta t_2}, r_{v_x}^{\Delta t_3}, \dots r_{v_x}^{\Delta t_{m'}}), L_x \notin L$
$M = \{Model_1, Model_2, \dots, Model_m\}$
Output:
D_x: Predicted Destination of L_x

1: **function** Predict(L_x, M)
2: $i \leftarrow |L_x|$
3: ▷Get the length of current trace L_x.
4: $D_x \leftarrow$ Predict(Model$_i$, L_x)
5: ▷ Predict the destination of trace L_x with
6: $Model_i$.
7: **return** D_x
8: **end function**

of v_x. In the training stage, the purpose is to get different prediction models that fit for predicted traces of different lengths. Thus, the first step is to clip each trace to various lengths and add them to different training sets, with function Select(L, i, *destination*), as shown in line 4. Next, with each training set, a proper training function, such as Bayes or LSTM model, is chosen to train the prediction model, as shown in line 7. Then in this stage, m models are obtained to be used in the prediction stage.

In the prediction stage, the length of the current trace is computed in order to select a proper prediction model whose feature length is the same as the trace length, as shown in line 2. When i is less or equal to the maximum value of model feature length, just select a proper model to predict the destination directly. Otherwise, only the first m locations in L_x are clipped and with the $model_m$, its destination can be predicted, as shown in line 4.

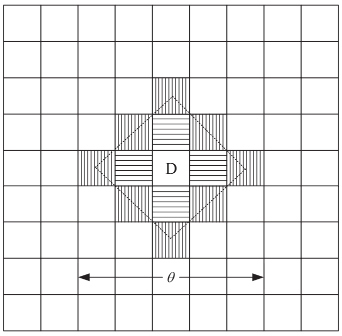

FIGURE 3. Computation of accuracy profit.

B. PROFIT MAXIMIZATION ALGORITHM

1) ACCURACY PROFIT AND FORWARDING PROFIT

Once the destination referring to a trace is predicted, how to evaluate the degree of accuracy on prediction is another problem. As the assumption in Section III-A, all the RSUs are distributed evenly as grids. As shown in Fig.3, the destination grid is in the center, and the prediction location may locate in or around the destination grid. As a message related to the destination area can affect vehicles in the surrounding grids, the conception of effective range θ is defined as the length between the two farthest, effective grids. Then, the Accuracy Profit can be formulated as equation 11.

$$AP = \begin{cases} 1 - \dfrac{2d(pre, des)}{\theta + 1}, & d(pre, des) < (\theta + 1)/2 \\ 0, & otherwise \end{cases} \tag{11}$$

Here, $d(pre, des)$ means the distance between predicted destination and the true destination, where Manhattan distance [27] is used to evaluate the distance.

Take $\theta = 5$ as an example. If the predicted destination is the same as the true destination, the Accuracy Profit is 1, which means the accuracy is 100%; if the predicted destination locates in the vertical line area, the Accuracy Profit is $1/3$, which means the prediction is partly accurate; if the predicted destination locates outside the shadow area, the Accuracy Profit is 0, which means not accurate.

In addition, we define a new evaluation factor – Forwarding Profit, which is used to evaluate the forwarding opportunities of a vehicle. As the factor is dependent on the number of neighbors of a vehicle, the Forwarding Profit can be formulated as equation 12. $N(v_i)$ is the number of neighbors v_i encounters.

$$FP = \begin{cases} \log(10 + N(v_i)), & d(pre, des) < (\theta + 1)/2 \\ 0, & otherwise \end{cases} \tag{12}$$

The definition follows the following rules. First, if the destination predicted is outside the shadow area, the forwarding profit is 0; otherwise, the forwarding profit is no smaller than 1. Second, with the number of neighbors increasing, the forwarding profit also increases. At last, when the number of neighbors is large, its effect on the forwarding profit becomes smaller. Thus, the increasing rate becomes smaller.

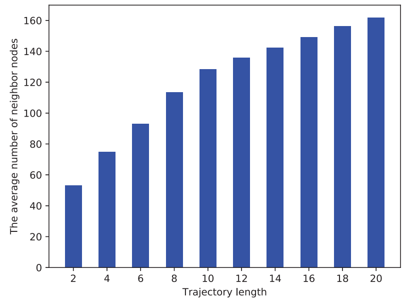

FIGURE 4. Relationship between the average number of neighbor nodes and the trajectory length.

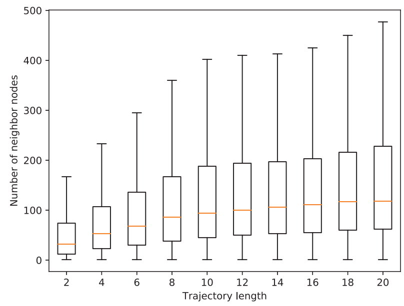

FIGURE 5. Boxplot on the median of neighbor nodes with the trajectory length.

2) EMPIRICAL STUDY ON THE AMOUNT OF VEHICLE NEIGHBORS

It is hoped that a vehicle can receive its destination related information as early as possible in order to spread the information to its neighbors, as some of its neighbors may have the same destination or interest with the vehicle itself. Before proposing a mechanism to solve this problem, we make an intuitive study on the number of neighbors of each vehicle.

We take a data set of taxi trajectories as the research data and the details about the data set is described in Section V-A. With this data set, we study the relationship between the trajectory length and the number of neighbors on each vehicle. As shown in Fig. 4 and Fig. 5, with the trajectory length increasing, both the average and the median on the number of neighbors are increasing. In other words, a vehicle may encounter more neighbor vehicles while it is traveling longer. Thus, it can be found that if the information is sent to a vehicle earlier, the information can be spread to its neighbors as many as possible.

3) DELIVERY PROFIT MAXIMIZATION ALGORITHM

While a vehicle is traveling to its destination, the service providers calculate its destination based on its current traveling trace. Once the destination is predicted, the service providers will send its destination related information as soon as possible. To solve this problem, intuitively, the destination of a vehicle should be predicted as early as possible, and then its destination related information can be spread widely. Besides, the destination prediction should be as accurate as possible, then the information delivered is useful. Thus, a Delivery Profit Maximization Algorithm is proposed to solve this problem, shown in Algorithm 3. In addition, when the bandwidth of an RSU is not enough for every vehicle in its coverage to communicate, a Communication Scheduling Algorithm as shown in Algorithm 4 is also proposed.

Algorithm 3 Delivery Profit Maximization Algorithm

Input:
$L_k = (r_{v_k}^{\Delta t_1}, r_{v_k}^{\Delta t_2}, r_{v_k}^{\Delta t_3}, \ldots r_{v_k}^{\Delta t_m})$
$M = \{Model_1, Model_2, \ldots, Model_i\}$
Output:
$r_{v_k}^{\Delta t_x}$ ($r_{v_k}^{\Delta t_x} \in L_k$): A location in L_k

1: **function** DeliveryProfitMax(L_k, S)
2: **for** $\Delta t_x \leftarrow \Delta t_1$ *to* Δt_m **do**
3: Dis = DestinationDistance(L_k, Δt_x, M)
4: **if** $Dis \leq \phi$ and DestinationDistance(L_k, $\Delta t_x + 1$, M) $\leq Dis$ **then**
5: **return** $r_{v_k}^{\Delta t_x+1}$
6: **end if**
7: **end for**
8: **return** NULL
9: **end function**
10:
11: **function** DestinationDistance(L_k, Δt_x, S)
12: $CurLoc \leftarrow r_{v_k}^{\Delta t_x}$
13: $CurTrace \leftarrow Clip(L_k, \Delta t_x)$
14: $i \leftarrow |CurTrace|$
15: $PreDes \leftarrow Predict(Model_i, CurTrace)$
16: $DestinationDistance \leftarrow d(CurLoc, PreDes)$
17: **return** *DestinationDistance*
18: **end function**

Algorithm 3 is sketched as follows. Given the trace L_k of vehicle v_k and the model set of destination prediction, a proper location $r_{v_k}^{\Delta t_x}$ in the trace can be selected to be the best location to send information. There are two functions in the algorithm, including DELIVERYPROFITMAX function used to find the best location and DESTINATIONDISTANCE function used to calculate the distance between the current location and the predicted destination. In line 2, it means while the vehicle is traveling, it will pass by each location one after one. At each location, the service providers collect a vehicle's previous trace and predict its destination with its current trace and related model (shown in line 3). If the distance between the predicted destination and its current location is not greater than ϕ and the distance between the next predicted destination and its next location is also not greater than the previous distance, the next location should be selected as the message dissemination location, because it is traveling closer to the destination and the prediction is accurate. If none of the locations passed by satisfies the above conditions, no location is selected and the algorithm will return NULL as shown in line 8. In function DESTINATIONDISTANCE, from the line 13 to the line 14, the two steps are preparing for the destination prediction. Once the

Algorithm 4 Communication Scheduling Algorithm

Input:
w_{r_k}: Bandwidth of RSU r_k
$V = \{v_1, v_2, \ldots, v_n\}$: Vehicles in the coverage area of r_k
$PreD = \{PreD_{v_1}, \ldots, PreD_{v_n}\}$: Predicted destination of each vehicle in V
$C = \{C_{v_1}, C_{v_2}, \ldots, C_{v_n}\}$: Bandwidth cost for each vehicle communication
Output:
$V' \subseteq V$: Vehicles the RSU can send messages to

1: **function** ComScheduling(w_{r_k}, V, $PreD$, C)
2: **while** $V \neq \emptyset$ **do**
3: **for** v_x in V **do**
4: Find v_i with $min\{d(r_k, PreD_{v_i})\}$
5: **end for**
6: **if** $C_{v_i} \leq w_{r_k}$ **then**
7: $V' \leftarrow V' \cup \{v_i\}$
8: $w_{r_k} \leftarrow w_{r_k} - C_{v_i}$
9: **end if**
10: $V \leftarrow V - \{v_i\}$
11: **end while**
12: **return** V'
13: **end function**

destination is predicted in line 15, the distance between the predicted destination and its current location is returned. In this algorithm, the parameter ϕ is variable and its value will have effect on the algorithm, so that it is evaluated in section V.

When an appropriate location for message dissemination is selected for each vehicle through Algorithm 3, the delivery sequence in the coverage range of an RSU should be scheduled by Algorithm 4. The main idea of Algorithm 4 is to select the vehicle with the minimum distance to its destination to deliver messages first. The algorithm is sketched as follows. Given the bandwidth of an RSU r_k, each vehicle's predicted destination and communication bandwidth cost, a sequence of vehicles that can be sent messages is obtained. First, in the vehicle set, a vehicle v_i with the minimum distance to its destination can be found, as shown in line 2-4. Then if the communication bandwidth cost C_{v_i} is not greater than the RSU's available bandwidth w_{r_k}, vehicle v_i is selected to communicate. Remove v_i from V and add it to V', as shown in line 5-9. Repeat the above process until V is empty.

V. SIMULATIONS

A. DATA SET DESCRIPTION

Our experimental data is based on the GPS data of taxis in Shenzhen, China. It is continuously sampled by the GPS device with frequency $1/60Hz$ during time period 2011/04/18-2011/04/26. Due to the noise in the data set, we do some data processing work, which is described as follows.

(1) We regard the longitude range in [113.800,114.300] and latitude range in [22.450,22.700], which is the coverage range

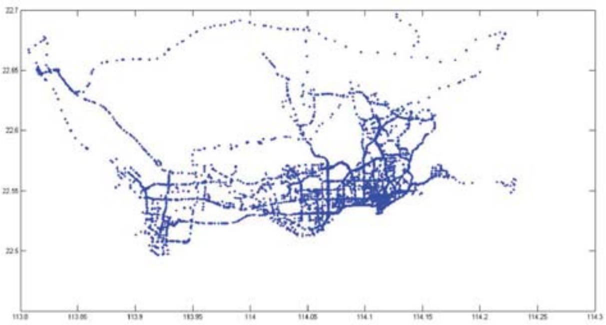

FIGURE 6. Screenshot of vehicle locations at a time slot.

of Shenzhen, as our focus area. Trajectories outside of this area are removed to guarantee our experiment results.

(2) Some location shakes with a long distance in trajectories are considered to be noise data and removed.

(3) The trajectories with long traveling distance take up only a small part of the total data set. So trajectories with length larger than 20km are removed to guarantee the experimental results.

After processing the data, there are 13798 taxis and at a random time slot, a screenshot of vehicle locations is shown in Fig.6. The number of trajectories is 878028, of which 733840 pieces of trajectories are less than 10km. The distribution of the trajectory lengths is shown in Fig. 7. It can be found that most of trajectory lengths are between 2km and 6km and with the trajectory length increasing, the amount of trajectories falls down.

B. SIMULATION PARAMETERS AND RESULTS

There are two scenarios in our simulation part, including the destination prediction scenario and the RSU scheduling scenario.

1) DESTINATION PREDICTION SCENARIO

a: SIMULATION PARAMETERS

First, we test our destination prediction algorithm in order to fix the destination prediction models. Thus, we take LSTM model and Bayes model as the *TrainFunction* in Algorithm 1 to train our prediction models. As the amount of long trajectories is small, which is not enough to train an accurate prediction model, we just consider the trajectory length of no more than 10km. Then 724893 pieces of trajectories are

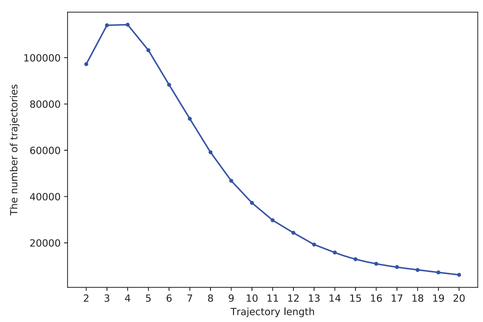

FIGURE 7. Distribution of the trajectory length.

selected, which are composed of eight groups of trajectories with length varying from 3 to 10. Referring to the parameters on LSTM model, the number of layers is set to 7 which shows it performs better than the other number of layers. The number of neurons in each layer is set to 15 times of the number of features. We adopt two methods to prevent overfitting. One is setting dropout parameter which is set to 0.2. The other one is to use 'earlystop' method, which means training is stopped immediately when the overfitting takes place. We use mean squared error(MSE) as loss function that monitors the loss.

Each group of traces is divided to two parts, with one fifth as the testing set and the other as the training set. We use LSTM and Bayes models to train each group of traces and with the testing set to verify the accuracy. There are two kinds of testing sets. First we use the trajectories of length 10 to test all the models with Algorithm 2. When the number of model features evaluated is less than the trajectory length, the first several locations in the trajectory with the same number as model features are selected. This case is called 'realtime', as shown in Fig. 8, which is used to simulate the process of service providers' realtime prediction. Second, all the trajectories with the length no larger than the number of tested model features are selected to evaluate the model, which is called 'offline'.

b: SIMULATION RESULTS

In Fig. 8, it can be found that when a vehicle just starts to move, it is hard to predict its destination with both the LSTM model and Bayes Model. However, with its traveling to the destination, the prediction accuracies of both models increase. This phenomenon is reasonable for that when a vehicle starts to travel, it can travel to any destination, which is hard to be predicted. When it is closed to the destination, the destination of the trip is easier to be observed.

In addition, it is found that the accuracies on offline data testing set are usually higher than that on realtime data testing set. For example, when the trajectory length is 3, the accuracies of offline test and realtime test for Bayes model are 20% and 10% respectively. In offline data set, the testing trajectories contain those trajectories with length between the feature length of the current model and the largest trajectory length. In other words, some short trajectories in the data set improve the accuracy for both LSTM model and Bayes model. However, LSTM model performs always better than Bayes model, so that in the following scenario, we use LSTM model to perform destination prediction for vehicles.

2) RSU SCHEDULING SCENARIO

a: SIMULATION PARAMETERS

This scenario is to evaluate the RSU scheduling mechanism, namely delivery profit maximization algorithm. Here, we take LSTM model as the *TrainFunction* in Algorithm 1 to train our prediction models and perform the prediction

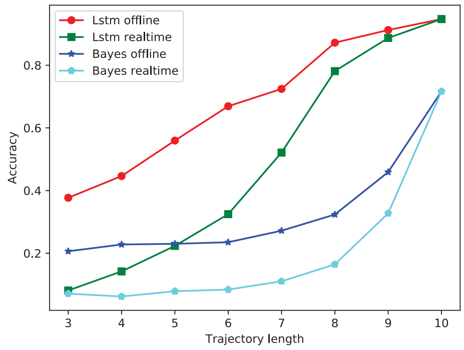

FIGURE 8. **Prediction accuracy of Bayes and LSTM models.**

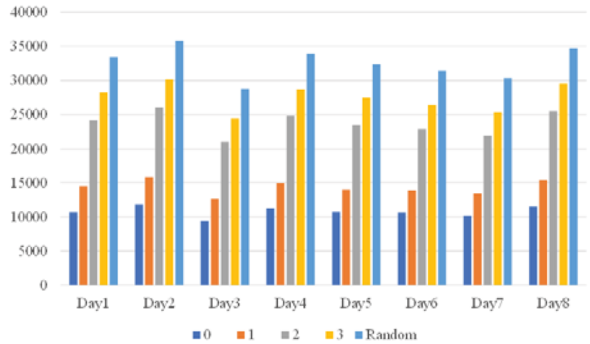

FIGURE 9. **Accuracy profit for Various Mechanisms on Each Day($\theta = 7$, $bandwidth = unlimited$).**

process. The trajectories of 8 days are utilized to make the simulation. While each vehicle is traveling, the service providers can monitor their traces and always make realtime predictions on their destinations. Once a proper time or location is selected, the destination related information should be sent from the service provider to the vehicle through an RSU.

To evaluate Algorithm 3, we compare it with the mechanism of randomly sending. In the randomly sending mechanism, the service provider randomly selects a location in its trajectory to predict the destination and then sends the destination related information through the RSU. Here, the same prediction model is used for both mechanisms, to evaluate the RSU scheduling mechanism and the 'random' mechanism. In the scenario, the effective range θ is set to 7, with ϕ as 0, 1, 2, 3. Besides, the bandwidth of each RSU is assumed to be unlimited first, so that each RSU can communicate with multi-vehicles simultaneously. Then the total delivery profit, the average delivery profit, the total forwarding profit and the average forwarding profit for each mechanism can be obtained to evaluate the algorithm. At last, the bandwidth is considered and we set the bandwidth to be 1 in order to test the performance of Algorithm 4, with other parameters the same.

b: EVALUATION METRICS

There are four objectives to be evaluated – total accuracy profit, average accuracy profit, total forwarding profit and the

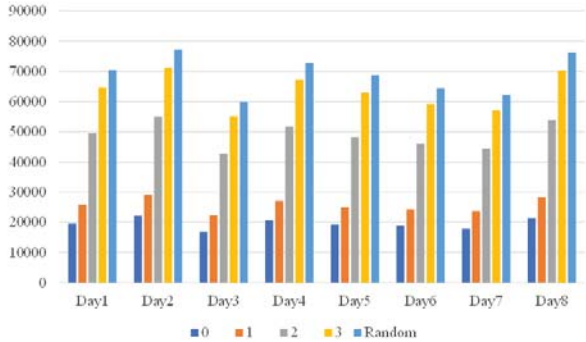

FIGURE 10. **Forwarding profit for various mechanisms on each day($\theta = 7$, $bandwidth = unlimited$).**

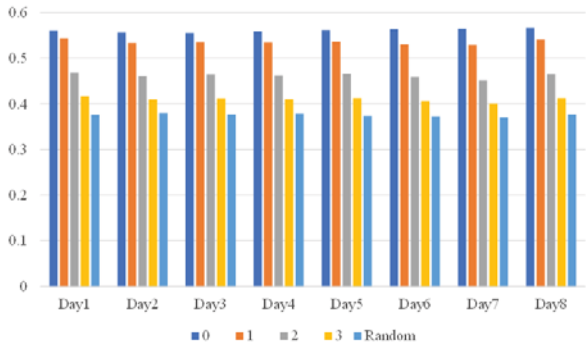

FIGURE 11. **Average Accuracy rate for various mechanisms on each day($\theta = 7$, $bandwidth = unlimited$).**

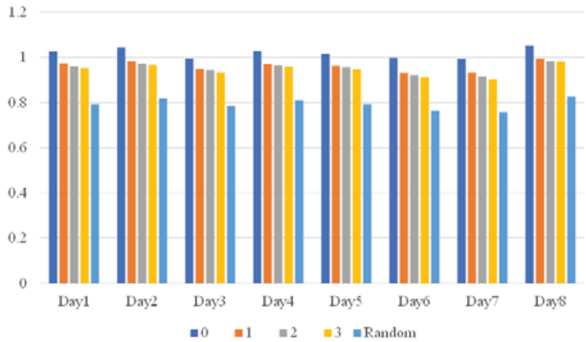

FIGURE 12. **Average forwarding rate for various mechanisms on each day($\theta = 7$, $bandwidth = unlimited$).**

average forwarding profit. To evaluate various mechanisms in term of the four objectives, we use a function of multi-object optimization, shown in formula 13. Here, $obj(k)$ is the value of the k-th object on a mechanism and $obj(k)_{ideal}$ is the ideal value of the objective. All the values should be normalized before applying formula 13. Its main idea is to calculate the distance between the current value and the ideal value of each objective. Then the distance is multiplied by a weight to obtain the *Deviation*, with w_k being 0.25. Based on equation 13, the smaller the deviation is, the better the mechanism is.

$$Deviation = \sum_{k=1}^{4} w_k * [\frac{obj(k) - obj(k)_{ideal}}{obj(k)_{ideal}}]^2 \tag{13}$$

TABLE 1. Evaluation of delivery profit with $\theta = 7$, *bandwidth* = *unlimited*.

Day \ ϕ	0	1	2	3	Random
1	0.986	0.726	0.194	0.101	0.160
2	0.960	0.706	0.191	0.107	0.147
3	0.971	0.714	0.186	0.101	0.148
4	0.957	0.712	0.189	0.105	0.148
5	0.966	0.731	0.196	0.105	0.160
6	0.941	0.709	0.197	0.118	0.169
7	0.953	0.704	0.205	0.126	0.175
8	0.968	0.711	0.194	0.108	0.159

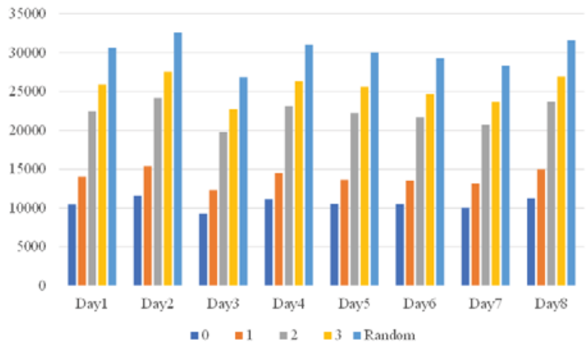

FIGURE 13. Accuracy profit for various mechanisms on each day($\theta = 7$, *bandwidth* = 1).

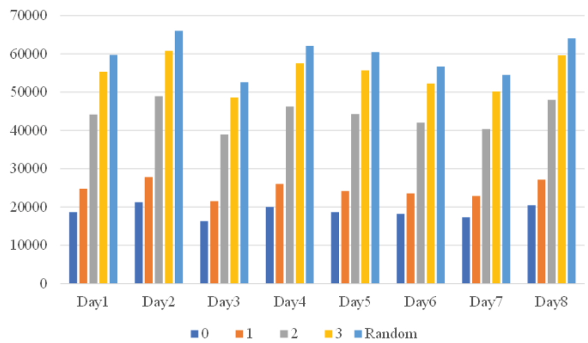

FIGURE 14. Forwarding profit for various mechanisms on each day($\theta = 7$, *bandwidth* = 1).

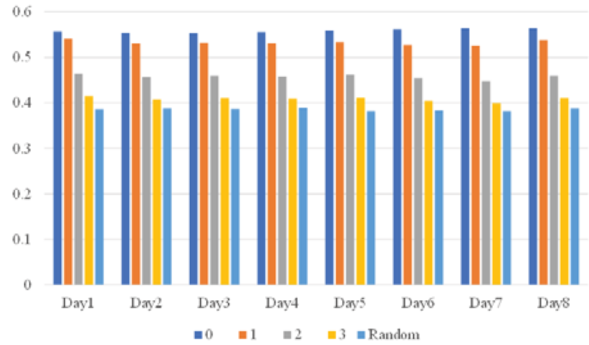

FIGURE 15. Average accuracy rate for various mechanisms on each day($\theta = 7$, *bandwidth* = 1).

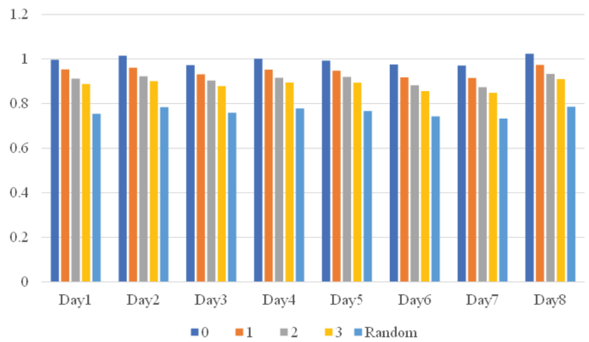

FIGURE 16. Average forwarding rate for various mechanisms on each day($\theta = 7$, *bandwidth* = 1).

TABLE 2. Evaluation of delivery profit with $\theta = 7$, *bandwidth* = 1.

Day \ ϕ	0	1	2	3	Random
1	0.906	0.639	0.173	0.106	0.153
2	0.874	0.618	0.172	0.113	0.142
3	0.903	0.645	0.169	0.105	0.139
4	0.871	0.624	0.168	0.110	0.140
5	0.899	0.661	0.175	0.109	0.153
6	0.874	0.637	0.181	0.124	0.158
7	0.883	0.632	0.192	0.135	0.165
8	0.875	0.612	0.168	0.113	0.152

c: SIMULATION RESULTS

When the bandwidth is not considered, and $\theta = 7$, the trending statuses of the four objectives on each day are almost the same, as shown from Fig.9 to Fig.12. Thus, it can be believed that the performance of each value of ϕ is stable. In terms of accuracy profit and the forwarding profit, they increase with ϕ ascending and the random mechanism performs better than the others. In terms of average accuracy profit and the average forwarding profit, they decrease with ϕ ascending and the random mechanism performs worst. As shown in table 2, with multi-object optimization, when the value of ϕ is 3, the deviation is the smallest, which means this case is best for the overall four objectives and the random mechanism performs worse.

When the bandwidth is considered, we take the bandwidth = 1 as the simulation parameter. The trending statuses of the four objectives on each day are almost the same as the case of unlimited bandwidth, as shown from Fig.13 to Fig.16. However, comparing to the case of unlimited bandwidth, the accuracy profit and the forwarding profit are smaller, when the bandwidth is 1, as some vehicles cannot receive destination related messages, due to limited bandwidth. However, when the value of ϕ is 3, it stills performs best. Overall, our algorithms perform better than the mechanism of randomness, while the value of ϕ is 3, in terms of the four objectives.

VI. CONCLUSION AND FUTURE WORK

This paper targets the scenario that how the destination related information is disseminated in IoVs by service providers. In this scenario, vehicles don't share their destination information actively to other people, including service providers. Thus, the main problem is to predict the destination of each vehicle and select a proper time slot to deliver the destination related information to vehicles. In order to solve this problem, we first propose a realtime destination prediction framework which is based on the machine learning models. In our simulation on predictions, the prediction accuracy with LSTM model can achieve 94%, which is better than with Bayes model. Based on this prediction framework, we propose two algorithms to select a proper slot to disseminate destination related messages. With the algorithms, a proper slot in vehicles' trips can be found, that optimizes the accuracy profit and the forwarding profit. Simulations on the algorithms are deployed. The results show that when the value of ϕ is 3 for θ being 7, the overall objectives are satisfied best. However, the algorithm is based on the prediction results, thus the accuracy of destination prediction affects the delivery profit. In order to improve the delivery profit, the prediction accuracy should be improved, which is the future research direction.

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