On Exploring the Carrying-Charging Demand Balance in Cruising Route Recommendation for Vacant Electric Taxis

Linfeng Liu, Jiaqi Yan, and Jia Xu

***Abstract*—As the gasoline taxis are gradually restricted due to the increased environmental awareness, electric taxis (E-taxis) have become a more environmentally friendly choice to provide the transportation service. When some E-taxis are vacant, they typically cruise along roads without any specific destinations, and two major concerns should be considered for vacant E-taxis: In order to increase the business profits of E-taxis, it is vital to recommend the profitable cruising routes along which vacant E-taxis could pick up passengers as early as possible and earn more profits. Besides, the residual electricity of E-taxis is continuously consumed on travels, and E-taxis must be timely charged before their residual electricity is exhausted (i.e. the breakdowns of E-taxis). Thus, the cruising route recommendation for vacant E-taxis should take into account both passenger-carrying demand and charging demand, and the carrying-charging demand balance should be properly made. To this end, we propose a cruising Route Recommendation Method based on Carrying-charging Demand Balance (RRM-CDB) for vacant E-taxis. The passenger-carrying demand and charging demand are first formulated to reflect their changes and interrelationships, and the historical cruising trajectories of vacant E-taxis (with the two types of demand) are locally learned to recommend the future cruising routes, because the historical cruising trajectories contain the distribution of taxi demand of passengers and the trend of vacant E-taxis gradually approaching the charging stations with the decrease of residual electricity. Particularly, in RRM-CDB each vacant E-taxi trains a local learning model in a distributed manner, thus significantly reducing the computational complexity of cruising route recommendation. Extensive simulations and comparisons demonstrate that RRM-CDB can help to increase the business profits of E-taxis and avoid the breakdowns of E-taxis as much as possible.**

***Index Terms*—Electric taxis; cruising route recommendation; carrying-charging demand balance; maximization of business profits.**

I. Introduction

In recent years, the market share of Electric Vehicles (EVs) has been growing rapidly as the environmental awareness increases. Currently, many cities are implementing restrictions on gasoline vehicles. Taxis, being an essential component of the public transportation system, can offer enhanced flexibility in the transportation service [1], [2]. As the gasoline taxis are gradually restricted, electric taxis (E-taxis) have become a more environmentally friendly choice [3].

The development of vehicular battery technique has largely prolonged the endurance mileage of E-taxis and mitigated the range anxiety of drivers. Nonetheless, compared to gasoline taxis, E-taxis still face the range anxiety [4] while also caring about their business profits. The major challenges of E-taxis include: (*i*) The endurance mileage of E-taxis is typically shorter than that of gasoline taxis; (*ii*) The charging time of E-taxis is much longer than the refueling time of gasoline taxis; (*iii*) The long charging time of E-taxis could lead to the long queuing at charging stations. Fortunately, the battery exchange manner [5] has been proposed in recent years, enabling E-taxis to directly replace the vehicular batteries with fully charged ones at the charging stations, and this manner can effectively shorten the charging time and extend the service time of E-taxis. However, the range anxiety of drivers still exists due to the short endurance mileage of E-taxis. Hence, E-taxis typically concern the State Of Charge (SOC) and the future business profits especially when they are vacant (not carrying any passengers) and cruise along roads without specific destinations.

If vacant E-taxis [1] attempt to pick up more passengers, and only consider the charging demand when the residual electricity is about to be exhausted, then the E-taxis with low SOC could be quite far away from the charging stations, making E-taxis easy to break down on roads; On the contrary, if vacant E-taxis always cruise around some charging stations due to the serious range anxiety, then their business profits could be largely reduced.

Therefore, in order to increase the business profits of E-taxis while mitigating the range anxiety, it is vital to provide vacant E-taxis with proper cruising route recommendation based on the passenger-carrying demand and charging demand. As illustrated in Fig. 1, when a passenger is hailing the E-taxis, it makes a hailing request to the order server. A vacant E-taxi falling into the hailing range of the passenger could be assigned by the order server to pick up the passenger. When the SOC of a vacant E-taxi remains high, the cruising route should be constituted by the roads with high taxi demand. However, the charging demand of a vacant E-taxi is gradually increased with the

L. Liu, J. Yan, and J. Xu are with the School of Computer Science and Technology, Nanjing University of Posts and Telecommunications, Nanjing 210023, China, and also with the Jiangsu Key Laboratory of Big Data Security and Intelligent Processing, Nanjing 210023, China.

[1]Occupied E-taxis do not consider the charging demand because they must deliver the carried passengers to the destinations as soon as possible.

decrease of SOC. When the SOC of the vacant E-taxi becomes low, it could have both passenger-carrying demand and charging demand simultaneously, and the cruising route should be constituted by the roads with high taxi demand while approaching the charging stations gradually.

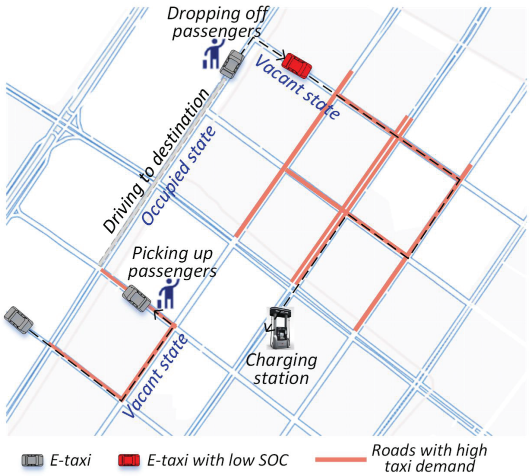

Fig. 1: An example of cruising routes for a vacant E-taxi.

Thanks to the continuous advancement of positioning technology [6], Beidou navigation or GPS has been widely equipped by E-taxis, and thus the historical cruising trajectories of E-taxis, pick-up locations, and drop-off locations can be easily recorded. Some valuable information can be explored from these records, e.g., the distribution of taxi demand of passengers, and the trend of vacant E-taxis gradually approaching the charging stations with the decrease of residual electricity. The cruising route recommendation for vacant E-taxis must address the following key issues:

(*a*) Taxi demand of passengers exhibits evident fluctuations across different areas during different time intervals. For instance, there is high taxi demand in the densely populated areas during the morning rush hours, and the taxi demand in the areas near office buildings increases during the evening rush hours. As the essential demand of E-taxis, the passenger-carrying demand can be inferred according to the time-varying distribution of the taxi demand of passengers which can be learned from the historical cruising trajectories of E-taxis.

(*b*) While a vacant E-taxi is cruising, the charging demand increases as its residual electricity decreases. There is a risk that the mileage displayed by the dashboard of the E-taxi could be incorrect, which could make the E-taxi exhaust the residual electricity and break down on roads. Moreover, due to the traffic jams and other emergencies, E-taxis (with low SOC) far away from the charging stations are easy to break down on roads. To reduce the risk of E-taxis exhausting the residual electricity before arriving at the charging stations, the cruising routes for vacant E-taxis should gradually approach the nearby charging stations as the residual electricity decreases.

(*c*) How to model and measure the passenger-carrying demand and charging demand jointly is another issue. The charging demand of an E-taxi is primarily associated with the residual electricity. The passenger-carrying demand of an E-taxi is related to the passenger-carrying state, i.e., the E-taxi has the passenger-carrying demand when it is vacant. Note that the passenger-carrying demand and charging demand are mutually exclusive, since vacant E-taxis are usually difficult to seek for the passengers and charging service simultaneously.

Motivated by the above issues, we propose a cruising Route Recommendation Method based on Carrying-charging Demand Balance (RRM-CDB), where the passenger-carrying demand and charging demand of vacant E-taxis are taken into account jointly. Fig. 2 illustrates the framework of RRM-CDB:

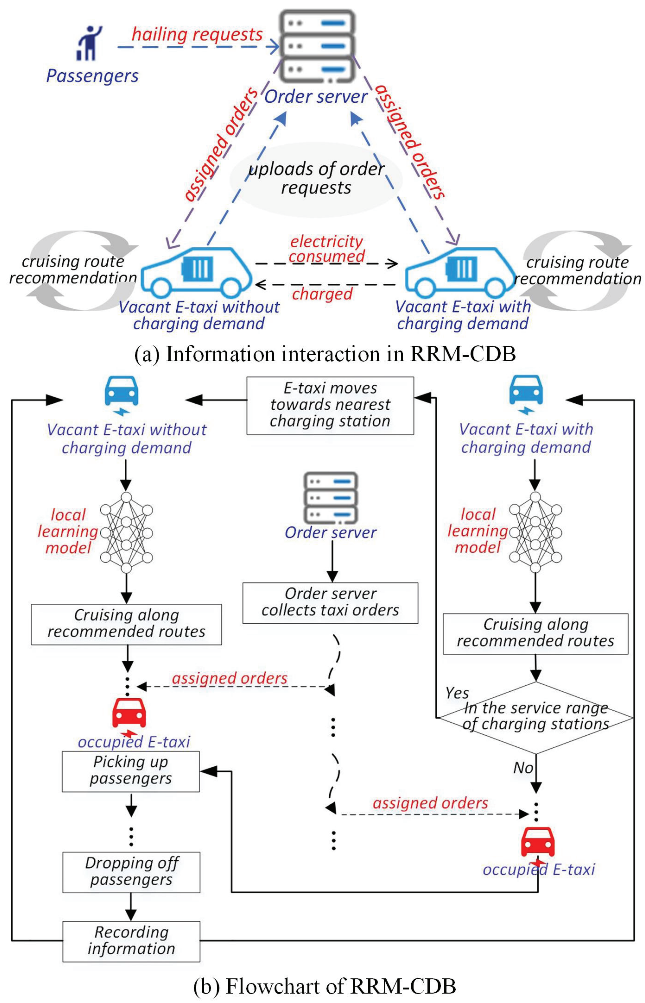

Fig. 2: Framework of RRM-CDB.

- With regard to the passengers to be served by E-taxis, they make hailing requests to the order sever and wait for the assignments of vacant E-taxis.
- With regard to the order server, it receives the hailing requests from passengers and the order requests from vacant E-taxis. The order server should assign proper vacant E-taxis to pick up the passengers.
- With regard to the E-taxis, they record some information (historical cruising trajectories, pick-up loca-

tions, and drop-off locations) and detect the residual electricity. Each E-taxi trains a local learning model (with an encoder-decoder architecture) by learning the local historical cruising trajectories, since the encoder-decoder architecture performs well in handling the sequential data (e.g. trajectories), and can capture the spatio-temporal relationships in the sequential data effectively [7]. The cruising routes of vacant E-taxis are locally recommended by their local learning models whose input mainly contains the passenger-carrying demand and charging demand.

Specifically, the encoder in the local learning model is composed of self-attention layer, residual connection, Temporal Convolutional Networks (TCNs) [8], and Long Short-Term Memory modules (LSTMs), and the decoder is composed of self-attention layer, residual connection, and LSTMs. Thus, some valuable information hidden in the historical cruising trajectories, e.g., the distribution of taxi demand of passengers and the trend of vacant E-taxis gradually approaching the charging stations with the decrease of residual electricity, can be effectively explored for the cruising route recommendation.

The remainder of this paper is organized as follows: Section II briefly surveys some existing related studies. Section III formulates the problem of cruising route recommendation for vacant E-taxis. Section IV provides the details of the proposed RRM-CDB. Section V covers some analyses of RRM-CDB. Simulation results for performance evaluation of RRM-CDB are reported in Section VI. Finally, Section VII concludes the paper.

II. Related Work

A. Route recommendation for taxis or E-taxis

With regard to the cruising route recommendation for vacant E-taxis, there are two critical concerns:

(i) The business profits of E-taxis. In order to earn more profits, taxis (E-taxis) are typically recommended to move towards the areas with high taxi demand. Many literatures have been devoted to the issue of route recommendation for taxis. For example, [9] designs an adaptive deep reinforcement learning method to fuse the spatio-temporal features to recommend the dynamic routes for taxis. [10] provides a particle-based model to consider the real-time travels of the relevant components in a transportation system. In [11], a Markov decision process is used to model the taxi service strategy, and optimize this strategy by considering the charging constraints of E-taxis. Lai $et\ al.$ [12] propose the urban traffic Coulomb's law, which is applied to model the relationship between taxis and passengers. The vacant taxis are routed to the optimal road segments to pick up the desired passengers by calculating the traffic attraction and traffic force. Besides, by learning the raw GPS trajectories of gasoline taxis, [13] builds a probabilistic Action-Based Tree (ABT), which is employed to recommend the routes for E-taxis with an effective speeding-up strategy. In [14], a method called FairMove is developed to improve the overall profit efficiency and the profit fairness of E-taxi fleets.

(ii) The charging demand of E-taxis. The work in [15] develops a game-theoretical approach for E-taxis to select the charging stations, which can reduce the travelling time and queuing time of E-taxis with enough fairness. A multi-agent Mean Field Hierarchical Reinforcement Learning (MFHRL) framework is proposed in [16]. MFHRL sets some goals for the agents to effectively learn the far-sighted charging decisions and relocation decisions. E-taxis can go to a battery swapping station and replace their empty batteries with full-charged ones, which is an efficient and fast recharging manner. Furthermore, [17] gives a hybrid charging management framework by jointly considering the combination of plug-in charging and battery swapping. The method is able to guide E-taxis to appropriate charging stations according to the charging demand.

We can get some inspirations from the above works for exploring the problem of cruising route recommendation of vacant E-taxis. However, the cruising route recommendation which can balance the passenger-carrying demand and charging demand has not been carefully investigated in the above works.

B. Learning methods in route recommendation

Recently, some learning methods have demonstrated the great advantages in solving the problem of route recommendation. Based on some learning methods, the historical information regarding E-taxis can be exploited for the cruising route recommendation. For example, Qu $et\ al.$ [18] propose a profitable taxi route recommendation method called Adaptive Shortest Expected cruising Route (ASER). ASER uses the Kalman filtering method to predict the pick-up probability and the capacity of locations. Besides, ASER takes into account the load balance between passengers and taxis, and the term "shortest expected cruising distance" is introduced to formulate the potential cruising distance of taxis. Based on the route classes obtained by trajectory clustering, the prediction method of pedestrian paths named PoPPL is proposed in [19] to predict the destination regions through a bidirectional LSTM classification network, and then generates the future trajectories.

[20] provides a Spatio-Temporal Digraph Convolutional Network model (STDCN). The input of STDCN is a directed spatio-temporal graph constituted by the pick-up locations and drop-off locations. STDCN has good performance in extracting the dynamic spatio-temporal features. [21] develops a robust and scalable approach that integrates a reinforcement learning component and a centralized programming structure to promote the real-time operations of taxis. The decomposed state-value function is learned by the reinforcement learning component. Likewise, in [22], a deep reinforcement learning based approach is proposed to dispatch vacant taxis to the areas with high taxi demand. In addition, [23] provides a deep learning-based model which integrates Graph Convolution Network (GCN) and LSTM. The pick-up probability on each road segment with the consideration of potential taxi oversupply can be accurately predicted by the GCN-LSTM model. In [24], a Recurrent

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Neural Network (RNN) approach is presented, and the semantics of visited locations are encoded according to the geographical information of location-based social networks.

C. Motivation of our work

If vacant E-taxis cruise along roads casually, then the business profits of E-taxis are reduced, and the pick-up conflicts [2] among vacant E-taxis are easily caused. More importantly, some E-taxis could break down on roads when they cannot be timely charged (e.g., they are far away from the charging stations when they detect the low SOC). To this end, the business profits (passenger-carrying demand) and the range anxiety (charging demand) are taken as the major concerns in this paper.

III. Problem Formulation

We first describe the problem of cruising route recommendation for vacant E-taxis. Due to the time-varying demand, we divide an observation period (e.g. a day) into some discrete time intervals with an equal length of θ_a, and each time interval is divided into some discrete time slots with an equal length of θ_s, as depicted in Fig. 3.

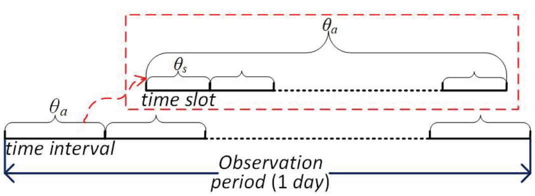

Fig. 3: Time interval and time slot.

TABLE I shows the list of main notations. Some relevant definitions regarding the problem of cruising route recommendation are given as follows:

TABLE I: Main notations

Notation	Description
$\mathcal{V}$	Set of E-taxis
$\mathcal{S}$	Set of charging stations
$e_i^{(t)}$	Residual electricity of E-taxi v_i at the t-th time slot
$\varphi_i^{(t)}$	State (occupied or vacant) of E-taxi v_i at the t-th time slot
$w^{(t)}$	Weather condition at the t-th time slot
R_h	Hailing range of each passenger
R_c	Service range of each charging station
l_m	The m-th location vector
$(l_{m+1}, \cdots, l_{m+n})$	A recommended cruising route
$F(v_i, t)$	Route feature of E-taxi v_i at the t-th time slot
$\mathcal{T}(v_i, t)$	Historical cruising trajectory of E-taxi v_i at the t-th time slot
$Pft(v_i)$	Total business profit earned by E-taxi v_i
$Inc(v_i, T_k)$	Business income of E-taxi v_i paid by carried passengers during the time interval T_k
$Csm(v_i, T_k)$	Electricity consumed by E-taxi v_i on travels during the time interval T_k
$\mathscr{O}(l_s, l_e)$	Taxi order with the departure point l_s and the destination point l_e
$\mathcal{I}(l_s, l_e)$	Set of road intersections travelling from l_s to l_e
r_p	Price of an E-taxi carrying passengers per kilometer
r_0	Unit price of electricity purchased from power grid
c	Electricity consumption for an E-taxi travelling through a unit distance
ϵ	Loose charging threshold
ε	Strict charging threshold

A. E-taxis

Suppose there are N E-taxis travelling on the road network, and the set of E-taxis is denoted by $\mathcal{V}$. The total business profit earned by E-taxi v_i during an observation period is calculated by:

$$Pft(v_i) = \sum_{k=1}^{\kappa} \left\{ Inc(v_i, T_k) - r_0 \cdot Csm(v_i, T_k) \right\}, \quad (1)$$

where κ denotes the number of time intervals during an observation period.

B. Local dataset of E-taxis

The local dataset of each E-taxi (e.g. v_i) includes: (i) Historical cruising trajectories of v_i when v_i was vacant. The historical cruising trajectories describe the processes of v_i from passenger findings to passenger pick-ups, which also reflect the historical taxi demand. The historical cruising trajectory of v_i at the t-th time slot is denoted by $\mathcal{T}(v_i, t)$. (ii) Historical residual electricity of v_i. The historical residual electricity reflects the historical variation of charging demand of v_i. The residual electricity of v_i at the t-th time slot is denoted by $e_i^{(t)}$. (iii) Historical weather conditions. Note that the taxi demand of passengers is strongly related to the weather conditions, and the weather condition at the t-th time slot is denoted by $w^{(t)}$.

The route feature of E-taxi v_i at the t-th time slot is defined as:

$$F(v_i, t) = \left\{ t, \mathcal{T}(v_i, t), \varphi_i^{(t)}, e_i^{(t)}, w^{(t)} \right\}, \quad (2)$$

where $\varphi_i^{(t)}$ denotes the occupied state of v_i (indicating that v_i is vacant or occupied). If v_i is occupied (carrying passengers) at the t-th time slot, then $\varphi_i^{(t)} = 1$; Otherwise $\varphi_i^{(t)} = 0$. When E-taxis are occupied, the charging demand is not considered to avoid the travel deviations of the carried passengers.

C. Route calculation

OSMnx [25] is used to download, model, analyze, and visualize the road network and other geo-spatial features from OpenStreetMap. In our simulations (Section VI), OSMnx is also employed to find the routes between different locations. For instance, as illustrated in Fig. 4, OSMnx finds the set of road intersections when travelling from l_s to l_e, denoted by $\mathcal{I}(l_s, l_e)$. The route is formed by sequentially connecting the road intersections in $\mathcal{I}(l_s, l_e)$.

[2]The pick-up conflicts of E-taxis refer to the situation that several vacant E-taxis could move towards the same locations and intend to pick up the same passengers.

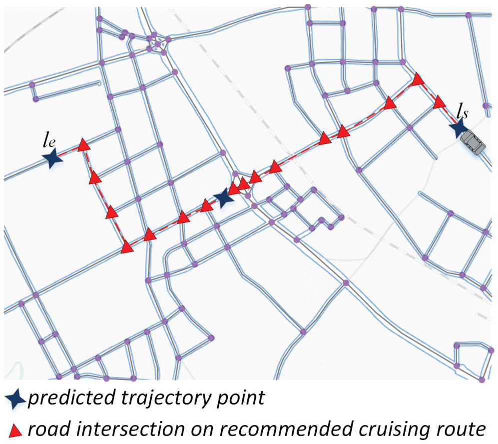

Fig. 4: A route obtained by OSMnx.

D. Order server and charging stations

The order server can receive taxi orders from passengers. $\mathscr{O}(l_s, l_e)$ represents the taxi order with the departure point l_s and the destination point l_e. While cruising, vacant E-taxis periodically upload the order requests to the order server. The hailing range of each passenger is denoted by R_h. The order server could assign the taxi orders to the vacant E-taxis falling into the hailing range of passengers.

For a vacant E-taxi v_i and a received taxi order, if the residual electricity of v_i can support the travel to the nearest charging station after completing the taxi order, and then the taxi order can be served by v_i. The set of taxi orders that can be served by each vacant E-taxi will be notified to the order server.

The set of charging stations is denoted by $\mathcal{S}$. A vacant E-taxi v_i with the charging demand can be charged at a charging station if v_i falls into the service range (R_c) of the charging station. As a special case, when the residual electricity of v_i reaches the strict charging threshold ε, v_i will travel to the nearest charging station, no matter whether v_i falls into the service range of a charging station or not.

E. Objective functions

To satisfy the passenger-carrying demand and charging demand, the recommended cruising routes should enable E-taxis to increase the business profits and avoid the breakdowns as much as possible. Therefore, we formally present the problem objectives as follows:

$$\begin{cases} \max \sum_{v_i \in \mathcal{V}} Pft(v_i), \\ \min \sum_{v_i \in \mathcal{V}} Bd(v_i), \end{cases} \tag{3}$$

where $Bd(v_i) = \begin{cases} 1, & \text{if } v_i \text{ breaks down}, \\ 0, & \text{otherwise}. \end{cases}$

$\max \sum_{v_i \in \mathcal{V}} Pft(v_i)$ indicates that the sum of business profits of all E-taxis needs to be maximized, i.e., the recommended cruising routes should help E-taxis to increase their business profits as much as possible. $\min \sum_{v_i \in \mathcal{V}} Bd(v_i)$ indicates that the proportion of E-taxis breaking down on roads needs to be reduced as much as possible. Essentially, the two objectives attempt to prolong the service time of E-taxis, consequently reducing the unnecessary electricity consumption and enhancing the efficiency of E-taxi resource.

IV. Cruising Route Recommendation based on Carrying-charging Demand Balance

E-taxis have the passenger-carrying demand when they are vacant, and E-taxis have the charging demand when their SOC is low.

A. Passenger-carrying demand and charging demand

Typically, the passenger-carrying demand and charging demand of E-taxis cannot be satisfied simultaneously, and thus the two types of demand are mutually exclusive.

The SOC (residual electricity) of E-taxis is the primary indicator to measure the charging demand of E-taxis, and the variation of charging demand is illustrated in Fig. 5, where ϵ and ε denote the loose charging threshold and strict charging threshold, respectively.

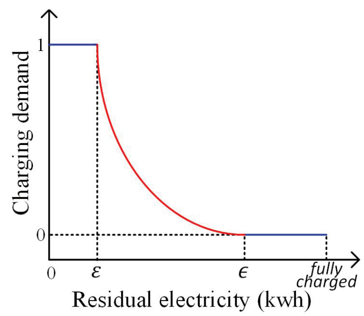

Fig. 5: Charging demand.

The values of ϵ and ε measure the charging urgency of E-taxis. When the residual electricity of an E-taxi is lower than ϵ, indicating that the E-taxi has the charging demand; When the residual electricity of an E-taxi is lower than ε, the E-taxi must urgently travel to the nearest charging station for charging, and the passenger-carrying demand is temporarily neglected before the charging.

The charging demand of E-taxi v_i at the t-th time slot is denoted by $Charge(v_i)^{(t)}$. When the residual electricity falls into the interval $[\varepsilon, \epsilon)$, $Charge(v_i)^{(t)}$ should be expressed as a convex function [4]. We define $Charge(v_i)^{(t)}$ as:

$$Charge(v_i)^{(t)} = \begin{cases} 0, & e_i^{(t)} \geq \epsilon, \\ \left(\frac{\epsilon - e_i^{(t)}}{\epsilon - \varepsilon}\right)^{\vartheta}, & \varepsilon \leq e_i^{(t)} < \epsilon, \\ 1, & e_i^{(t)} < \varepsilon, \end{cases} \tag{4}$$

where ϑ is a preset exponent related to the aging state of batteries, and then the passenger-carrying demand is written as $Carry(v_i)^{(t)} = 1 - Charge(v_i)^{(t)}$.

B. Local learning on vacant E-taxis

For the cruising route recommendation of vacant E-taxis, a local learning model is specially designed, as shown in

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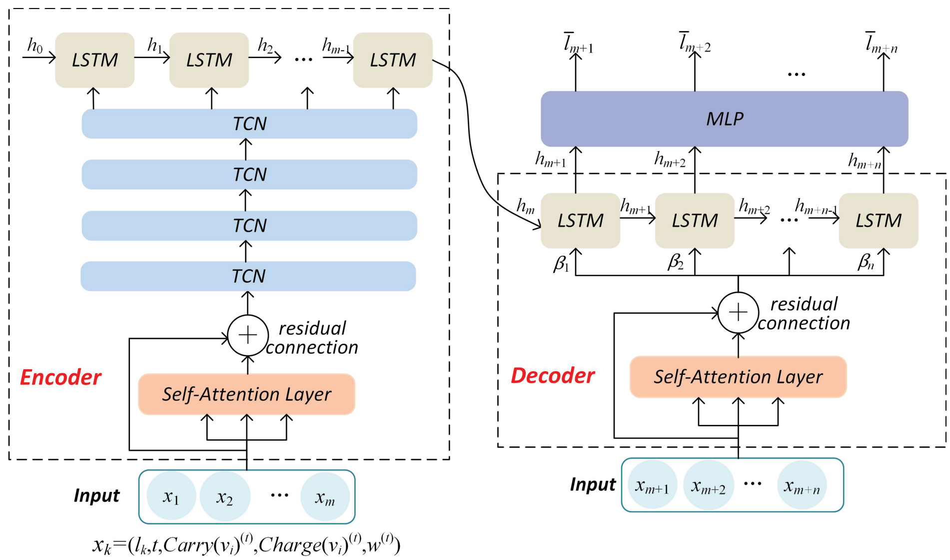

Fig. 6: Local learning model for cruising route recommendation.

Fig. 6. Firstly, the components, input, and output of the local learning model are described as follows:

- **Components**: The local learning model adopts an encoder-decoder architecture, where the encoder is composed of self-attention layer, residual connection, TCNs, and LSTMs, and the decoder is composed of self-attention layer, residual connection, and LSTMs.
- **Input**: $m + n$ trajectory points, where m trajectory points serve as the input of the encoder, and n trajectory points serve as the input of the decoder. Each trajectory point is expressed as a quintuple feature, which contains the location, time slot, passenger-carrying demand, charging demand, and weather condition. For example, the feature of a trajectory point x_k of E-taxi v_i is expressed as $(l_k, t, Carry(v_i)^{(t)}, Charge(v_i)^{(t)}, w^{(t)})$ (Fig. 6).
- **Output**: n future locations which constitute a recommended cruising route. As shown in Fig. 6, the recommended cruising route is expressed as the form $(\bar{l}_{m+1}, \cdots, \bar{l}_{m+n})$.

To recommend a cruising route that effectively balances the passenger-carrying demand and charging demand for a vacant E-taxi, we input the historical cruising trajectories into the model to yield the recommended cruising route. In the local learning model with encoder-decoder structure, the encoding process can be regarded as a dimensionality reduction representation of the input sequence. This dimensionality reduction helps to remove the redundant features and reserve the vital features in the historical cruising trajectories. The decoder can restore the historical cruising trajectories, allowing this model to maintain an understanding of the historical cruising trajectories after the dimensionality reduction.

In the encoder, the self-attention layer is capable of capturing both global information and local information from the input sequence. With the self-attention layer, the mobility patterns of E-taxis can be generalized from their historical cruising trajectories. Additionally, to mitigate the effect of gradient vanishing problem and gradient exploding problem, we add a residual connection behind the self-attention layer.

The intermediate results obtained from the residual connection are fed into TCNs for further processing. TCNs are particularly well-suited for handling the time-series tasks, allowing for mapping the input sequence of arbitrary length into the output sequence of the same length. Each TCN consists of several modules (dilated causal convolution and residual connection), as illustrated in Fig. 7.

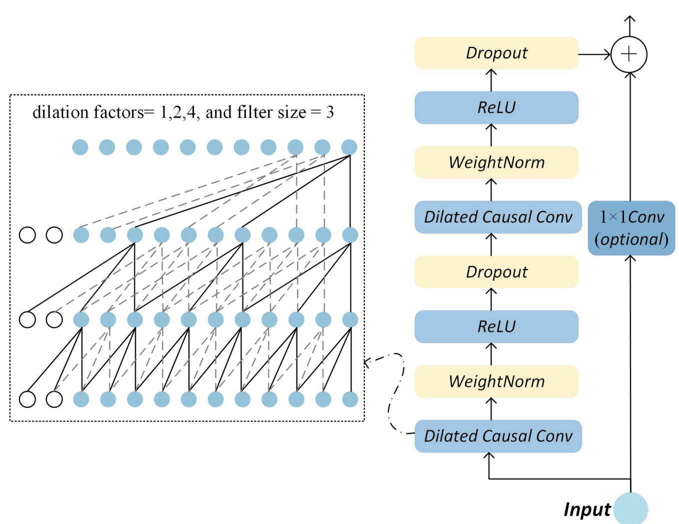

Fig. 7: Structure of a TCN.

Dilated causal convolution is strictly time-constrained, and it inserts a number of "holes" between pixels in the convolutional kernel. These holes or dilations effectively expand the perceptive field of the model, thus enhancing the ability of handling the extended time-series tasks. When TCNs are stacked in multiple layers, they further augment the network's perceptive field based on the sequential data, allowing for the extraction of features with long time scales. The last layer of the encoder is composed of several LSTMs which preserve the crucial features h_m from the output of the stacked TCNs.

The first LSTM in the decoder receives h_m (as well as the output of the residual connection within its own decoder) for the following computation:

$$\begin{cases} h_{m+1} = LSTM(h_m, \beta_1), \\ \vdots \\ h_{m+n} = LSTM(h_{m+n-1}, \beta_n). \end{cases} \tag{5}$$

The output of the decoder $(h_{m+1}, \cdots, h_{m+n})$ is used as the input of the Multi-Layer Perceptron (MLP). By this mechanism, the dimensionality of output can be reduced while preserving the essential information.

Different historical cruising trajectories in the training dataset could exhibit quite different importance, implying that different weights should be set for learning different historical cruising trajectories, thus optimally balancing the passenger-carrying demand and charging demand. To this end, the loss function is defined by:

$$Loss = \frac{1}{M} \sum_{k=1}^{M} \gamma_k \cdot (l_k - \bar{l}_k)^2, \tag{6}$$

where M denotes the number of trajectory points. l_k denotes the true location of the k-th trajectory point, and $\bar{l}_k$ denotes the predicted location of the k-th trajectory point. γ_k denotes the weight attached to the k-th trajectory point.

C. Cruising route recommendation for vacant E-taxis

To strike a balance between passenger-carrying demand and charging demand for vacant E-taxis, each E-taxi trains the local learning model by the local historical cruising trajectories. This model can predict the cruising route for each vacant E-taxi whose passenger-carrying demand and charging demand are time-varying.

The details of RRM-CDB are described by the following cases:

Case A: E-taxis only have the passenger-carrying demand.

When the residual electricity of a vacant E-taxi v_i satisfies that $e_i^{(t)} \geq \epsilon$, there are $Charge(v_i) = 0$ and $Carry(v_i) = 1$. v_i cruises along the recommended route (obtained by the local learning model, and this route can guide v_i to pick up passengers) and periodically uploads an order request to the order server.

Each passenger to be served by E-taxis will upload a taxi order to the order server. The order server sends the set of available taxi orders to v_i (v_i falls into the hailing range of the passengers in these taxi orders). v_i selects a taxi order (with the largest business profit for v_i) from the set of available taxi orders, and then notifies the order server of this selection.

Since the order server could send the same taxi order to several vacant E-taxis, it is possible that multiple vacant E-taxis select the same taxi order. Suppose a taxi order is selected by v_i and another vacant E-taxi $v_{i'}$, which could lead to a potential pick-up conflict, and the order server notifies v_i of the potential pick-up conflict and sends an updated set of available taxi orders to v_i (if the business profit of $v_{i'}$ earned from the taxi order is larger than that of v_i). If v_i currently does not receive any taxi orders, then v_i continues to cruise along the recommended route.

Case B: E-taxis have both passenger-carrying demand and charging demand.

When the residual electricity of a vacant E-taxi v_i satisfies that $\varepsilon \leq e_i^{(t)} < \epsilon$. v_i cruises along the recommended route obtained by the local learning model, periodically uploads the order request to the order server. Besides, v_i checks whether it is within the service range of any charging stations. Three sub-cases are further discussed as follows:

Sub-case $B.1$: The current location of v_i falls into the service range of one or more charging stations, and then v_i moves towards the nearest charging station. During the trip to the nearest charging station, v_i will not send the order request to the order server.

Sub-case $B.2$: The current location of v_i does not fall into the service range of any charging stations, and v_i receives some taxi orders from the order server. To prevent v_i from breaking down on roads, the available taxi orders that can be served by v_i must satisfy the following condition: After completing the taxi order, the residual electricity of v_i can support the travel to the nearest charging station for charging.

Sub-case $B.3$: The current location of v_i does not fall into the service range of any charging stations, and v_i does not receive any available taxi orders from the order server, v_i continues to cruise along the recommended route obtained by the local learning model.

Case C: E-taxis only have the charging demand.

When the residual electricity of a vacant E-taxi v_i satisfies that $e_i^{(t)} \leq \varepsilon$, only the charging demand is considered by v_i, i.e., there are $Charge(v_i) = 1$ and $Carry(v_i) = 0$. Under such case, v_i immediately moves towards the nearest charging station for charging, no matter whether v_i falls into the service range of any charging stations or not. In this case, the local learning model is not used.

The above three cases indicate that our proposed RRM-CDB attempts to make a tradeoff between the two objectives (the maximization of business profits and the avoidance of breakdowns) and achieve them simultaneously as much as possible. In the above cases, for a vacant E-taxi after the charging or the end of the previous recommended cruising route, a new cruising route will be recommended to the vacant E-taxi.

A sequential diagram of interaction between E-taxis and order server is given in Fig. 8. In Fig. 8, an E-taxi whose residual electricity falling into the interval

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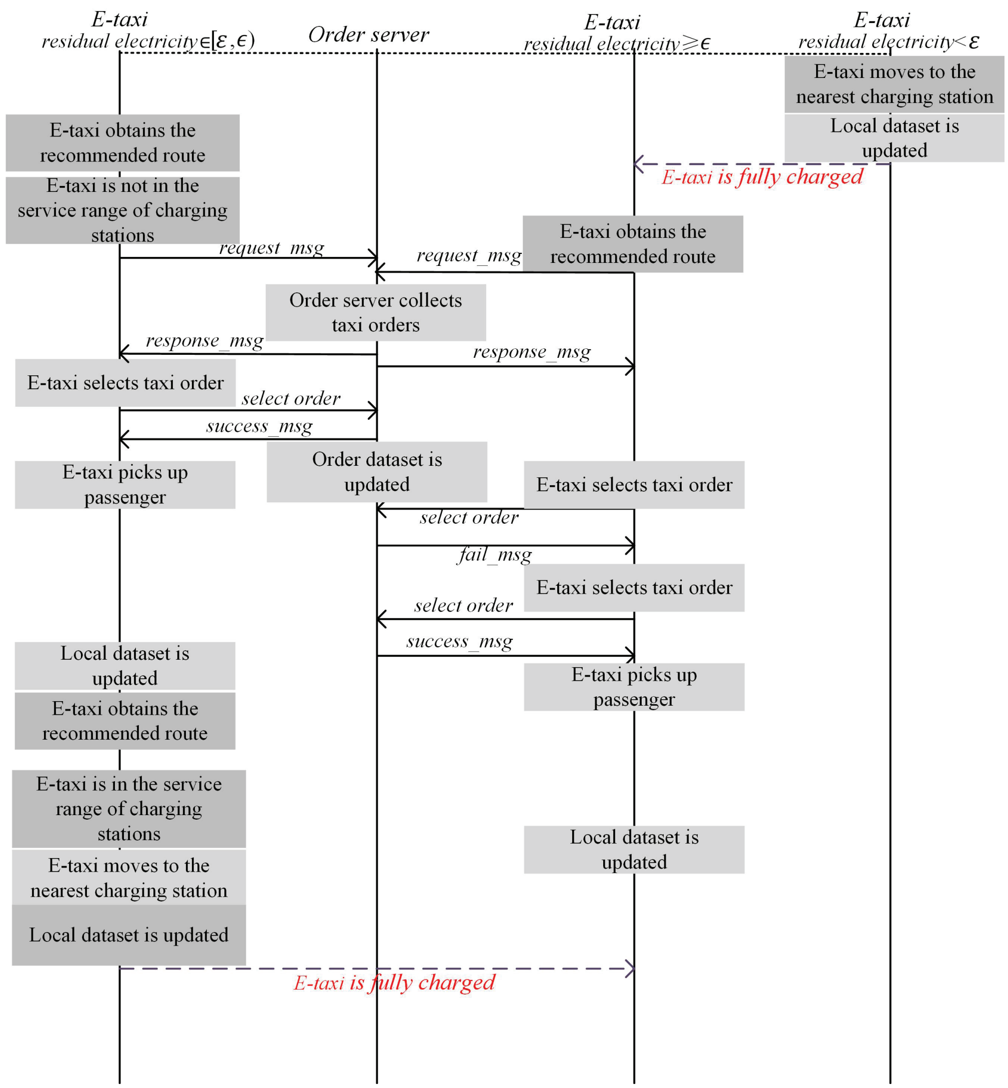


Fig. 8: A sequential diagram of interaction between E-taxis and the order server.

$[\varepsilon, \epsilon)$ sends a $request\_msg$ to the order server to request the available taxi orders. The order server responds with a $response\_msg$ containing the available taxi orders. Then, the E-taxi selects a taxi order and replies with a $select\_order$ to the order server. If the taxi order is approved by the order server, the order server will send back a $success\_msg$; Otherwise, the order server will send back a $fail\_msg$ and update the set of available taxi orders.

Note that RRM-CDB also attempts to enhance the processing efficiency and shorten the processing delay, by adopting the following three mechanisms: (i) Each E-taxi collects the data locally without the exchanges with others, thereby the communication complexity is reduced, and the communication delay is shortened. (ii) The local learning model on each E-taxi is trained by the local dataset in a distributed manner. Hence, the computational complexity of cruising route recommendation on each vacant E-taxi is reduced, and the processing efficiency is enhanced. (iii) The assignments of the proper vacant E-taxis for passengers are restricted by the hailing range of passengers, and thus the computational complexity of taxi order assignments is reduced.

V. Analysis of RRM-CDB

A. Complexity of RRM-CDB

The communications in RRM-CDB mainly involve some message interaction, e.g., the uploads of taxi orders from passengers, the uploads of order requests from vacant E-taxis, and the releases of available taxi orders from order server. Passengers upload the taxi orders to the order server, resulting in a communication load of up to $O(N_{pas})$, where N_{pas} denotes the number of passengers to be served by E-taxis. Additionally, vacant E-taxis upload the order requests to the order server, and the order server could release some available taxi orders to vacant E-taxis, indicating that the communication complexity reaches $O(N)$ in the worst case. Consequently, the communication complexity of RRM-CDB is of $O(N + N_{pas})$.

With regard to the computational complexity: Each E-taxi trains a local learning model, and the computational complexity of training the local learning model is related to the number of model parameters. The local learning model in RRM-CDB mainly consists of self-attention layer, TCNs and LSTMs. The computational complexity of training the self-attention layer is approximatively written as $O(m^2+n^2)$, as analyzed in [26]. The computational complexity of each TCN is mainly determined by dilated causal convolution, and is expressed as $O(\sum_{k=1}^{D} F_k^2 \cdot H_k^2 \cdot C_{k-1} \cdot C_k)$, where D denotes the number of layers of dilated causal convolution, F_k denotes the spatial size of the feature map in the k-th layer, H_k denotes the size of the filter in the k-th layer, C_{k-1} denotes the input channel in the k-th layer, and C_k denotes the output channel in the k-th layer. The computational complexity of each LSTM is written as $O(C_D \cdot N_h + N_h^2 + N_h)$, where C_D denotes the dimension of input, and N_h denotes the dimension of each hidden layer. Thus, by training the local learning models, the total amount of computations is expressed as $O(N \cdot (m^2+n^2+C_D \cdot N_h + N_h^2 + N_h + \sum_{k=1}^{D} F_k^2 \cdot H_k^2 \cdot C_{k-1} \cdot C_k))$. Typically, N_h is much larger than C_D, m, and n. Thus, the local learning models can capture the features from the input trajectory points as more as possible. Therefore, the computational complexity of RRM-CDB is of $O(N \cdot (N_h^2 + \sum_{k=1}^{D} F_k^2 \cdot H_k^2 \cdot C_{k-1} \cdot C_k))$.

B. Proportion of E-taxis breaking down and probability of E-taxis picking up passengers

In this section, we analyze the impacts of ε and ϵ on the proportion of E-taxis breaking down and the probability of E-taxis picking up passengers. Specially, the probability of E-taxis picking up passengers denotes the probability that a vacant E-taxi can pick up passengers before the residual electricity is lower than the strict charging threshold. Note that the business profits of E-taxis are strongly related to the probability of E-taxis picking up passengers.

Proposition 1: The proportion of E-taxis breaking down on roads is reduced by increasing ε or ϵ.

Proof: When a vacant E-taxi v_i has both passenger-carrying demand and charging demand, the charging demand at the t-th time slot $Charge(v_i)$ can be calculated by (4). To simplify the notation, we denote the charging demand of v_i by $\Im$ ($\Im = \left(\frac{\epsilon - e_i^{(t)}}{\epsilon - \varepsilon}\right)^{\vartheta}$), and thus the passenger-carrying demand of v_i is $1-\Im$.

The distance travelled by each E-taxi during a time slot is denoted by d. Consequently, the length of each recommended cruising route is written as $n \cdot d$, where n denotes the number of trajectory points in each recommended cruising route. The expectation of reduced distance from v_i to the nearest charging station after cruising along a recommended route is expressed as:

$$\mathbb{E}(\triangle D) = \sum_{num=1}^{n} \{\Im^{num} - (1-\Im)^{num}\} \cdot d. \tag{7}$$

Assuming that the distance from a vacant E-taxi to the nearest charging station obeys a Gaussian distribution $N(\mu_1, \delta_1^2)$, and hence the probability of v_i breaking down before reaching the nearest charging station is expressed as:

$$\begin{aligned} &P\left(X - \mathbb{E}(\triangle D) > \frac{e_i^{(t)}}{c} - n \cdot d\right) \\ &= 1 - \Phi\left(\frac{\frac{e_i^{(t)}}{c} - n \cdot d + \mathbb{E}(\triangle D) - \mu_1}{\delta_1}\right), \end{aligned} \tag{8}$$

where $\left(\frac{e_i^{(t)}}{c} - n \cdot d\right)$ denotes the distance v_i can travel (with the residual electricity) after cruising along a recommended route.

Recall that $\Im = \left(\frac{\epsilon - e_i^{(t)}}{\epsilon - \varepsilon}\right)^{\vartheta}$, thus $\Im$ increases as ϵ increases. Since $\Im < 1$, $\mathbb{E}(\triangle D)$ increases as $\Im$ increases. With the increase of $\mathbb{E}(\triangle D)$, $P\left(X - \mathbb{E}(\triangle D) > \frac{e_i^{(t)}}{c} - n \cdot d\right)$ is decreased. Thus, the probability of a vacant E-taxi breaking down can be decreased by increasing ϵ. Likewise, the probability of a vacant E-taxi breaking down can also be decreased by increasing ε. Therefore, the proportion of E-taxis breaking down on roads can be reduced by increasing ε or ϵ. □

Proposition 2: The probability of E-taxis picking up passengers is reduced by increasing ε or ϵ.

Proof: The residual electricity of vacant E-taxis typically obeys a Gaussian distribution $N(\mu_2, \delta_2^2)$ [27]. Suppose there is a vacant E-taxi with the passenger-carrying demand $1-\Im$. Then, the probability of the E-taxi picking up passengers is expressed as:

$$\int_{\epsilon}^{B_c} \frac{\exp\left(\frac{-(x-\mu_2)^2}{2\delta_2^2}\right)}{\sqrt{2\pi} \cdot \delta_2} \mathrm{d}x + \int_{\varepsilon}^{\epsilon} \frac{\exp\left(\frac{-(x-\mu_2)^2}{2\delta_2^2}\right)}{\sqrt{2\pi} \cdot \delta_2} \cdot (1-\Im)\, \mathrm{d}x, \tag{9}$$

where B_c denotes the battery capacity of each E-taxi. (9) indicates that the probability of E-taxis picking up passengers is reduced by increasing ε or ϵ. □

The conclusions of Proposition 1 and Proposition 2 imply that the two objectives in (3) cannot be realized simultaneously, and a tradeoff (i.e. carrying-charging demand balance) between the business profits of E-taxis and the proportion of E-taxis breaking down on roads should be made by properly setting the values of ε and ϵ. In the next section, we will observe the performance variation of RRM-CDB under different values of ε and ϵ.

VI. Performance Evaluations

In this section, we provide comprehensive performance evaluations on our proposed RRM-CDB and compare it with some related training models and related methods. The simulations are conducted on a dataset released by Didi Corporation [28]. In this dataset, the trajectories are collected in October 2018 in Chengdu city, China. This dataset includes about 50 million data items (time stamps, latitudes, longitudes, occupied states, and taxi ID). Besides, we add the SOC values into this dataset. The SOC of each E-taxi is generated according to the initial battery electricity (fully charged battery) and the electricity consumption on the travels. Due to the information lack of residual electricity in the original dataset, we specially design a dataset-revamp process: at the beginning of the simulations, the vacant E-taxis without charging demand travel according to the movements of taxis in the original dataset, while the vacant E-taxis with charging demand travel according to RRM-CDB. During the dataset-revamp process, more historical cruising trajectories can be collected for the training of local learning models of E-taxis, and the following simulation results do not include the results generated in the dataset-revamp process.

The trajectories of N E-taxis are randomly selected from the dataset for the following simulations. G charging stations are evenly distributed on the road network. We develop a simulator using Python language, and the main parameter settings are provided in TABLE II.

Fig. 9 illustrates an example of RRM-CDB involving three vacant E-taxis. The E-taxis cruise along the recommended routes until they either pick up passengers or being charged at charging stations. After dropping off the passengers or being charged, E-taxis continue to cruise along the routes recommended by RRM-CDB. The recommended cruising routes are marked by solid lines, while the routes when E-taxis carrying passengers are marked by dashed lines.

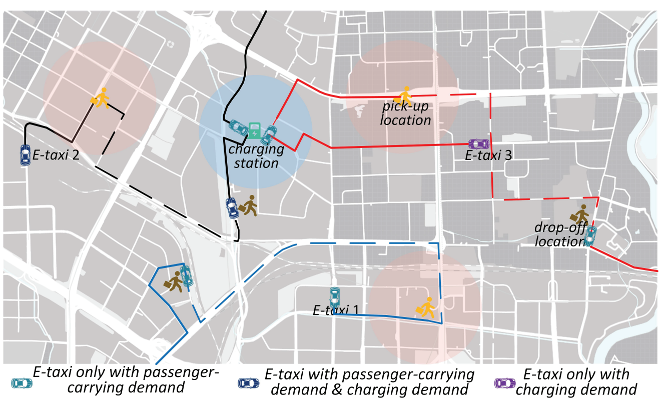


Fig. 9: An example of cruising routes recommended by RRM-CDB.

A. Comparisons among different learning models

We first measure the performance of RRM-CDB by two metrics: average business profit of E-taxis and average residual electricity of E-taxis when reaching the charging stations. In this section, we compare RRM-CDB with stacked-LSTM [29] and BiLSTM [30], as shown in Fig. 10. Specially, the average residual electricity of E-taxis is taken to measure the range anxiety of E-taxi drivers, i.e., E-taxis have more residual electricity when reaching charging stations, indicating that the range anxiety of their drivers is more relieved.

TABLE II: Simulation Parameters

Parameter	Description	Value
N	Number of E-taxis	200
G	Number of charging stations	6
θ_s	Length of each time slot	5 min
θ_a	Length of each time interval	60 min
R_c	Service range of each charging station	1.8 km
R_h	Hailing range of each passenger	1.5 km
κ	Number of time intervals during an observation period	24
m	Number of input trajectory points	22
n	Number of output trajectory points	3
Lr	Learning rate	0.001
B_c	Battery capacity of each E-taxi	60 kwh
c	Electricity consumption for an E-taxi travelling through a unit distance	0.5 kwh/km
r_0	Unit price of electricity purchased from power grid	0.7 CNY/kwh
r_p	Price of an E-taxi carrying passengers per kilometer	3 CNY/km
ϑ	Preset exponent in (4)	1.5
ϵ	Loose charging threshold	30 kwh
ε	Strict charging threshold	5 kwh

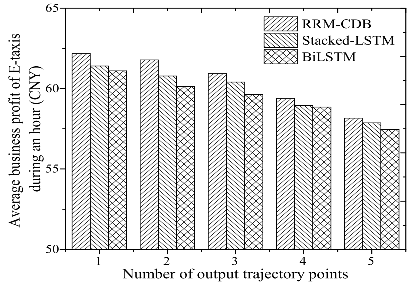
In Fig. 10(a), it is evident that the average business profit of E-taxis during an hour, obtained by three learning models, decreases as the number of output trajectory points increases, because the cruising routes recommended by these learning models are worsened when these models output more trajectory points. Notably, the learning model in our proposed RRM-CDB yields the largest average business profit of E-taxis. A similar trend is observed in Fig. 10(b), i.e., the average residual electricity of E-taxis when reaching the charging stations obtained by three learning models is decreased with the increase of n.

The above phenomena are attributed to the following reasons: Compared with stacked-LSTM and BiLSTM, RRM-CDB expands the perceptive field of the learning model, and can capture both global information and local information from the input trajectory points. Moreover, RRM-CDB possesses a deeper network to fit the input trajectory points and mitigate the effect of gradient vanishing problem and gradient exploding problem. Consequently, RRM-CDB demonstrates the superior handling of the input trajectory points, making it more suitable for the local learning on E-taxis.

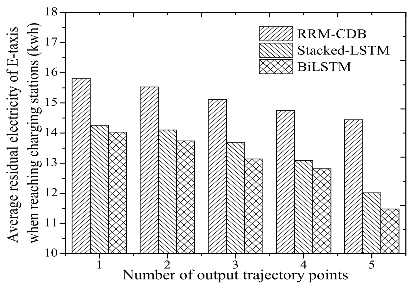
In RRM-CDB, a local learning model is applied to recommend the cruising routes for vacant E-taxis. To measure the training performance of the local learning model, we observe the loss value. In Fig. 11, RRM-CDB with a learning rate of 0.01 achieves the fastest convergence, while RRM-CDB with a learning rate of 0.0001 achieves the slowest convergence. Interestingly, with a learning rate of 0.001, RRM-CDB obtains the smallest loss value, implying that setting an appropriate learning rate is important for the training performance.

B. Average business profit of E-taxis

The relationship between the number of E-taxis and the average business profit of E-taxis is observed in Fig. 12.

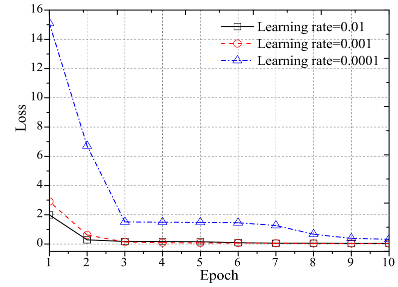


(a) Average business profit of E-taxis during an hour

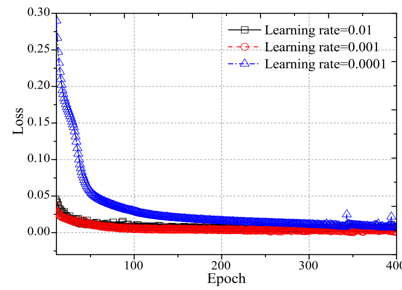


(b) Average residual electricity of E-taxis when reaching charging stations

Fig. 10: Comparisons among different learning models.



(a) Loss value (1 <Epoch$\leq$ 10)



(b) Loss value (10 <Epoch$\leq$ 400)

Fig. 11: Loss value vs. learning rate.

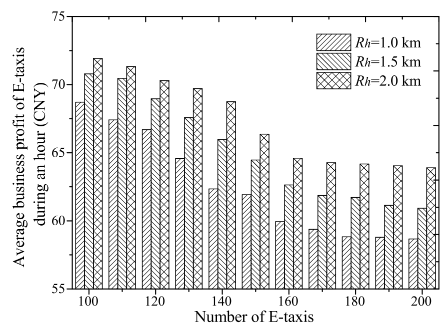


Fig. 12: Average business profit of E-taxis vs. N and R_h.

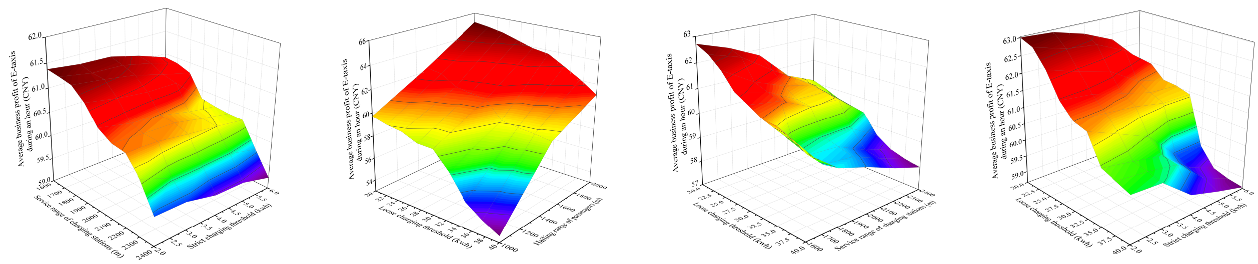
As N rises, the average business profit of E-taxis declines, which is attributed to the fact that a denser deployment of E-taxis could reduce the average number of taxi orders served by each E-taxi, thus decreasing the average business profit of E-taxis.

As shown in Fig. 13(a) and Fig. 15(b), the average business profit of E-taxis is reduced as R_c increases. Fig. 13(b) and Fig. 13(c) illustrate that the average business profit of E-taxis decreases as ϵ increases, and this is because a larger ϵ implies that E-taxis are considered to generate the charging demand when they have more residual electricity, i.e., E-taxis generate the charging demand earlier, and thus the service time of carrying passengers is shortened.

The impacts of ϵ and ε on the average business profit of E-taxis are observed in Fig. 13(d), where the average business profit of E-taxis gradually decreases with the increase of ϵ or ε, due to the following two reasons: (*i*) The increase of ϵ or ε leads to a reduction of service time of E-taxis; (*ii*) When ϵ or ε becomes larger, E-taxis could be charged more frequently, implying that E-taxis are prone to move close to charging stations and are farther away from passengers, and hence E-taxis have to travel longer distance to pick up the passengers. Note that the phenomena in Fig. 13(d) tally with the conclusion of Proposition 2 in Section V.B.

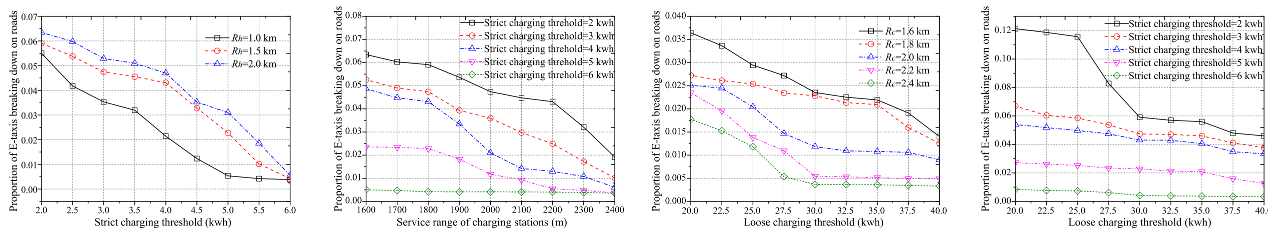
C. Proportion of E-taxis breaking down on roads

In Fig. 14, several observations are obtained: (*i*) In Fig. 14(a) and Fig. 14(d), the proportion of E-taxis breaking down on roads decreases as ε increases. Besides, the curve with a larger R_h is typically higher than that with a smaller R_h. This is because a larger ε allows E-taxis to move towards the charging stations when they have more residual electricity, thereby they are difficult to break down on roads. On the contrary, with a larger R_h, each vacant E-taxi can receive more taxi orders, emphasizing on the passenger-carrying demand and making it easier to break down on roads. (*ii*) In Fig. 14(b), the proportion of E-taxis breaking down on roads decreases as R_c increases. The reason is that a larger R_c allows E-taxis to respond to the charging demand more promptly, thus promoting the charging efficiency and reducing the breakdowns of E-taxis. (*iii*) In Fig. 14(c) and Fig. 14(d), with the increase of ϵ, the proportion of E-taxis breaking down is significantly reduced, since a larger ϵ indicates that E-taxis



(a) Average business profit of E-taxis vs. R_c and ε (b) Average business profit of E-taxis vs. ϵ and R_h (c) Average business profit of E-taxis vs. ϵ and R_c (d) Average business profit of E-taxis vs. ϵ and ε

Fig. 13: Average business profit of E-taxis during an hour.



(a) Proportion of E-taxis breaking down vs. ε and R_h (b) Proportion of E-taxis breaking down vs. R_c and ε (c) Proportion of E-taxis breaking down vs. ϵ and R_c (d) Proportion of E-taxis breaking down vs. ϵ and ε

Fig. 14: Proportion of E-taxis breaking down on roads.

should consider the charging demand when they have more residual electricity. The phenomena in Fig. 14(d) tally with the conclusion of Proposition 1 in Section V.B.

D. Impacts of service range and hailing range

A larger R_c indicates a larger service range of charging stations. Intuitively, E-taxis with charging demand, even those located farther from the charging stations, can approach the charging stations more timely under a larger R_c.

As depicted in Fig. 15, when R_c becomes larger, several key observations are obtained as follows: the average residual electricity of E-taxis when reaching the charging stations increases, the proportion of E-taxis breaking down on roads decreases, and the average business profit of E-taxis decreases. The reasons for these phenomena are as follows: (i) When the charging stations can provide larger-range charging service, E-taxis with charging demand are easier to fall into the service range of charging stations, and thus they can be charged more timely; (ii) Earlier charging also ensures that E-taxis reserve more residual electricity, effectively reducing the proportion of E-taxis breaking down on roads; (iii) Moreover, a larger R_c implies that E-taxis could travel longer distance to reach the charging stations, potentially shortening their service time and reducing their business profits.

Moreover, with an extended hailing range (a larger R_h), the order server can assign more available taxi orders to vacant E-taxis, which enables vacant E-taxis to serve more passengers, ultimately prolonging the service time and increasing the business profits. However, a larger R_h also leads to a decrease of the residual electricity of E-taxis when reaching the charging stations, making them difficult to be timely charged, and thus the proportion of E-taxis breaking down on roads is increased.

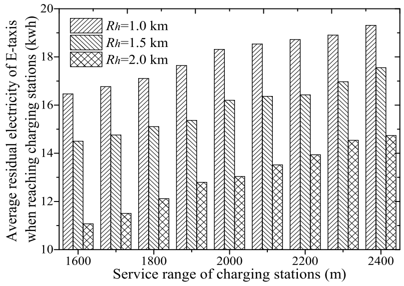
E. Performance of RRM-CDB under different weather conditions

The historical cruising trajectories under different weather conditions are extracted from the dataset for the simulations in this section.

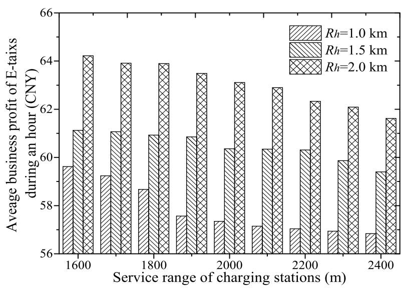
The taxi demand of passengers and road situations could vary with different weather conditions. Fig. 16(a) illustrates that E-taxis can obtain higher business profits during the overcast days and rainy days, compared to the sunny days and cloudy days. However, Fig. 16(b) shows a larger proportion of E-taxis breaking down on roads during the overcast days and rainy days. These observations can be attributed to the following facts: (i) During the overcast days and rainy days, more passengers prefer the taxi-travel manner over other public transport manners (such as buses or metros), resulting in a surge in the number of taxi orders. E-taxis can serve more passengers and thus increase their business profits. (ii) During the overcast days and rainy days, the presence of slippery roads significantly increases the driving difficulties of E-taxis, which leads to the heavy traffic congestion and increases the likelihood of E-taxis breaking down on roads.

F. Comparisons among different methods

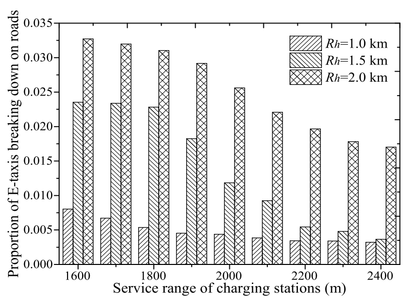
In Fig. 17, to further validate the merits of our proposed RRM-CDB, we compare RRM-CDB with some related



(a) Average residual electricity of E-taxis when reaching charging stations vs. R_c and R_h

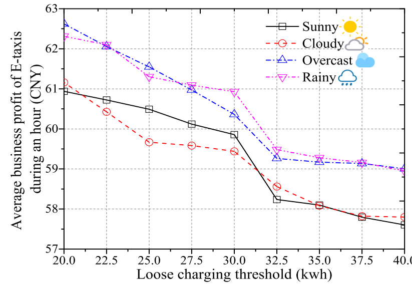


(b) Average business profit of E-taxis vs. R_c and R_h

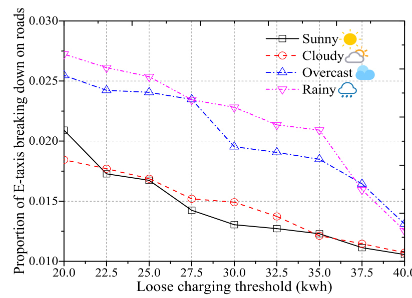


(c) Proportion of E-taxis breaking down on roads vs. R_c and R_h

Fig. 15: Impacts of service range of charging stations and hailing range of passengers.



(a) Average business profit of E-taxis



(b) Proportion of E-taxis breaking down on roads

Fig. 16: Performance of RRM-CDB under different weather conditions.

methods including Random Walk (vacant E-Taxis cruise randomly), ABT [13], PoPPL [19], and Priority Charging [3]. The simulation results demonstrate that RRM-CDB achieves the superior performance in terms of average business profit of E-taxis and proportion of E-taxis breaking down on roads.

Random Walk method performs the worst among these methods, indicating that the random movements of vacant E-taxis are irrational, and recommending the appropriate cruising routes for vacant E-taxis is essential.

Compared with PoPPL, RRM-CDB exhibits a stronger ability to learn the historical cruising trajectories. The average business profit of E-taxis obtained by RRM-CDB is larger than that obtained by PoPPL, and the proportion of E-taxis breaking down obtained by RRM-CDB is lower than that obtained by PoPPL.

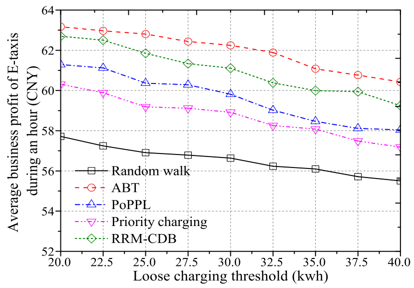
ABT typically focuses on the business profits by carrying passengers and overlooks the range anxiety of E-taxi drivers, while RRM-CDB attempts to balance the passenger-carrying demand and charging demand. Although ABT achieves a larger average business profit, the proportion of E-taxis breaking down obtained by ABT is much larger than that obtained by RRM-CDB. Note that the larger proportion of E-taxis breaking down will deteriorate the travel experience of E-taxi drivers more seriously.

Priority Charging method emphasizes the charging demand, enabling vacant E-taxis to follow the shortest routes to the charging stations after the charging demand is generated. Consequently, Priority Charging method obtains a smaller proportion of E-taxis breaking down than other methods, but the average business profit of E-taxis is much smaller than those of ABT, PoPPL, and RRM-CDB.

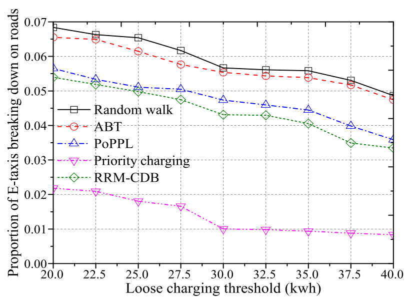
RRM-CDB recommends the cruising routes for vacant E-taxis by balancing the passenger-carrying demand and charging demand, and thus makes a preferable tradeoff between average business profit of E-taxis and proportion of E-taxis breaking down. When $\epsilon = 40$ kwh, the average business profit of E-taxis and the proportion of E-taxis breaking down obtained by RRM-CDB is equal to 59.25 CNY and 3.35%, respectively.

Note that the road network in Chengdu city is well-known for the large density, high complexity, and large

[3]When an E-taxi does not have the charging demand, the cruising route guides it to the area with the highest taxi demand; Otherwise, the cruising route guides it to the nearest charging station.



(a) Average business profit of E-taxis



(b) Proportion of E-taxis breaking down

Fig. 17: Comparisons among different methods (when ε=4 kwh).

number of intersections. Besides, the local learning model in RRM-CDB has the ability of adapting to various road conditions, traffic patterns, and driving behaviors, and the diversiform road segments do not affect the assignments of taxi orders. The above facts indicate that RRM-CDB can be easily extended for other types of road networks, other cities, and other geographical/urban settings.

VII. Conclusion

We have studied the problem of cruising route recommendation for vacant E-taxis, and a cruising Route Recommendation Method based on Carrying-charging Demand Balance (RRM-CDB) has been proposed. In RRM-CDB, the passenger-carrying demand and charging demand are firstly formulated, and the cruising routes are recommended by locally learning the historical cruising trajectories of vacant E-taxis. Specifically, the cruising routes are generated by jointly considering the distribution of taxi demand of passengers and the trend of vacant E-taxis gradually approaching the charging stations with the decrease of residual electricity. RRM-CDB helps to increase the business profits of E-taxis and reduce the proportion of E-taxis breaking down on roads.

Several practical issues need to be considered in future work: (i) The cruising routes recommended by RRM-CDB could guide the nearby vacant E-taxis to the same areas with high taxi demand, which could lead to the aggregation of vacant E-taxis and cause the pick-up conflicts among them. The pick-up conflicts of E-taxis could increase the useless energy consumption of E-taxis and reduce the efficiency of E-taxi resource. (ii) More electricity could be consumed due to some traffic events (e.g. traffic jams), and hence the proportion of E-taxis breaking down on roads can be reduced if the real-time traffic events are detected and considered in the cruising route recommendation. (iii) Some recorded data could be inaccurate, due to the faults of positioning devices, or the intense electromagnetic interference around positioning devices. The inaccurate data could affect the effectiveness of RRM-CDB seriously. Under such case, we can explore the regularities hidden in the historical data and filter the inaccurate data by some methods (such as K-fold cross-validation method). (iv) If some E-taxis break down on roads due to the electricity exhaustion, they could make the charging requests to some Mobile Charging Stations (MCSs) [31] which can offer prompt charging service for them.

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AUTHOR BIOGRAPHY

Linfeng Liu received the B. S. and Ph. D. degrees in computer science from the Southeast University, Nanjing, China, in 2003 and 2008, respectively. At present, he is a Professor in the School of Computer Science and Technology, Nanjing University of Posts and Telecommunications, China. His main research interests include the areas of vehicular ad hoc networks, wireless sensor networks and multi-hop mobile wireless networks. He has published more than 120 peer-reviewed papers in some technical journals or conference proceedings, such as IEEE TMC, IEEE TPDS, IEEE TIFS, IEEE TITS, IEEE TVT, IEEE TSC, ACM TAAS, ACM TOIT, Computer Networks, Elsevier JPDC. He has served as the TPC member of Globecom, ICONIP, VTC, WCSP.

Jiaqi Yan received the B. S. degree in computer science from the Nanjing University of Posts and Telecommunications in 2022. At present, she is a master student of Nanjing University of Posts and Telecommunications. Her current research interest includes the areas of vehicular networks and deep learning.

Jia Xu received the Ph. D. Degree in School of Computer Science and Engineering from Nanjing University of Science and Technology, Jiangsu, China, in 2010. He is currently a professor in Jiangsu Key Laboratory of Big Data Security and Intelligent Processing at Nanjing University of Posts and Telecommunications. His main research interests include crowdsourcing, edge computing and wireless sensor networks. Prof. Xu has served as the PC Co-Chair of SciSec 2019, Organizing Chair of ISKE 2017, TPC member of Globecom, ICC, MASS, ICNC, EDGE, and has served as the Publicity Co-Chair of SciSec 2021.