CD-Guide: A Reinforcement Learning based Dispatching and Charging Approach for Electric Taxicabs

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***Abstract*—Previous passenger demand inference methods have insufficient accuracy because they fail to catch the influence of all random factors (e.g., weather, holiday). Also, existing taxicab dispatching methods are not directly applicable for electric taxicabs because they cannot optimize their charging. We present *CD-Guide*: an electric taxicab dispatching and charging approach based on customized training and Reinforcement Learning (RL). We studied a metropolitan-scale taxicab dataset, and found: histogram of passengers' origin buildings (i.e., where they come from) is useful for selecting suitable training data for inference model, passenger demand in different regions may be influenced by various unpredictable random factors, and taxicabs' charging time must be considered to avoid missing potential passengers. By saying suitable historical data, we mean the data that are under the influence of random factors similar as current time. Then, we develop a RL based method to guide a taxicab to maximize its probability of picking up a passenger, minimize the number of its missed passengers due to charging, and meanwhile avoid the taxicab from battery exhaustion. Our trace-driven experiments show that compared with previous methods, *CD-Guide* increases the total number of served passengers by 100%.**

I. INTRODUCTION

In recent years, with ubiquitous mobility data harvested from the movement of the taxicabs, multiple urban passenger demand inference methods have been proposed [1], [2], [3], [4]. Generally, these methods utilize time series prediction methods (e.g., Autoregressive Integrated Moving Average (ARIMA)) or deep learning methods (e.g., Convolutional Neural Networks (CNN)) to learn taxicab passenger appearance pattern based on historical passenger pick-up records, and use the learned pattern to infer future passenger demand (i.e., the number of passengers at a future timestamp) at certain locations. However, they have insufficient accuracy because they fail to catch the influence of all random factors (e.g., weather, holiday). For example, suppose there is an electricity outage in a holiday parade, there may be a sudden peak of taxicab passenger demand near the parade position. Previous inference methods generally consider several obvious random factors such as weather and holiday, but it is impossible for them to list all random factors (e.g., electricity outage).

Meanwhile, based on the passenger demand inference result, various taxicab dispatching methods have been proposed [5], [6], [7], [8], [9]. These works generally focus on utilizing statistical models (e.g., hidden Markov chain) and routing methods (e.g., Dijkstra algorithm) to guide taxicabs to the locations with the maximum probability of potential passenger appearance through the shortest routes. However, all of these methods push taxicabs to cruise among locations where passengers are likely to appear, but are not directly applicable for electric taxicabs because they cannot optimize the charging of the taxicabs, which requires a relatively longer time. Some previous studies [10], [11], [12] have verified that electric taxicabs usually need to charge 2 to 3 times a day, and each charge lasts for 0.5 to 2.5 hours. Such a long bulk of idle charging time will cause the electric taxicabs to miss many potential passengers [13].

To overcome the drawbacks, we propose *CD-Guide*, an electric taxicab *C*harging and *D*ispatching approach, which utilizes customized selection and training of suitable historical passenger demands, and Reinforcement Learning (RL) to *Guide* an electric taxicab. By saying suitable historical data, we mean the data that are under the influence of random factors (e.g., weather, holiday) similar as current time. First, we analyzed a long-term metropolitan-scale taxicab mobility dataset that records the trajectories and passenger pick-up and drop-off activities of 15,610 taxicabs. We found that not all historical data are suitable for the passenger demand inference model, and the histogram of passengers' origin buildings (i.e., where the passengers come from) is a good indicator for identifying suitable historical data. Also, since passenger demand has different degrees of variance in different regions, the regions have different levels of maximum predicability of taxicab passenger demand (i.e., the maximum accuracy that a historical data training based inference method can possibly achieve), and the maximum predicability metric is a good indicator of the accuracy of the inference result.

The observations serve as the foundation for the design of *CD-Guide*. Specifically, for each passenger in the historical taxicab passenger demand data of a region, we first use the passenger's nearest building to identify the passenger (called the passenger's building tag). Then, we use the histogram of passengers' building tags to extract suitable historical training data in current time slot among different days, and then determine a linear regression based model to infer the demand value in the next time slot. Also, from the extracted suitable historical training data, we collect the distribution of possible trip lengths of the passengers in the next time slot to determine whether the taxicab's current SoC is able to serve future trips in the region. Subsequently, we utilize the entropy of previous passenger demand values, which is a metric for measuring the dissimilarity of the demand values, in each region to determine the maximum predictability of the region's future passenger demand value. Finally, for each taxicab that needs guidance on dispatching and charging, we first determine a candidate set of regions that the taxicab can reach with its current SoC, then we develop a RL based method for taxicab dispatching and charging to minimize the number of missed potential passengers caused by charging, maximize the probability of picking up a passenger, and meanwhile avoid the taxicab's SoC from exhaustion in the rest time of a day. In summary, our contributions include:

(1) We comprehensively study a metropolitan-scale taxicab dataset for insights on passenger demand, which serve as the foundation for the design of *CD-Guide*.

(2) We propose *CD-Guide*, an electric taxicab dispatching and charging approach. It first utilizes customized selection and training of suitable historical passenger demands to infer taxicab passenger demand in the next time slot for each region. Then, we develop a RL based method to optimize taxicab dispatching and charging.

(3) We have conducted extensive trace-driven experiments on the SUMO urban mobility simulator to show the effectiveness of *CD-Guide* in increasing the number of served passengers and avoiding the SoC of all taxicabs from exhaustion.

In our knowledge, *CD-Guide* is the first taxicab dispatching and charging method that maximizes the taxicab's probability of picking up a passenger, minimizes the number of missed potential passengers caused by charging, and meanwhile avoids the taxicab's SoC from exhaustion. The remainder of the paper is organized as follows. Section II presents literature review. Section III presents our metropolitan dataset measurement results. Section IV presents the detailed design of *CD-Guide*. Section V presents performance evaluation results. Section VI concludes the paper with remarks on our future work.

II. Related Work

Taxicab Passenger Demand Inference. Multiple urban passenger demand inference methods have been proposed. Fan *et al.* [3] proposed to decompose passenger demand into several patterns, and use the patterns to infer the number of population at specific times in each region. Shimosaka *et al.* [4] proposed to utilize a bilinear Poisson regression model to predict passenger demand in a metropolitan scale. Zhang *et al.* [1] developed a customized online training model with both historical and real-time GPS position data of taxicabs to infer taxicab passenger demand. Zhang *et al.* [2] proposed a residual Convolutional Neural Network (CNN) based model to learn the influence of several random factors (e.g., weather, period and trend of passenger demand), and achieved a higher inference accuracy than previous methods. However, these methods have insufficient accuracy because they fail to catch the influence of all random factors.

Taxicab Dispatching. Multiple taxicab dispatching works have been proposed. Yuan *et al.* [9] introduced a method that schedules the pick-up locations with the shortest routes for taxi drivers and the waiting locations for passengers to reduce the cruising time. Zheng *et al.* [7] modeled the driving patterns (e.g., driving path, parking position and time) of vacant taxicabs with a non-homogeneous Poisson process to find the optimal waiting positions for passengers. Zhang *et al.* [6] proposed a method to estimate the revenue of each route, and guide the taxicab to the route with the maximum estimated revenue. Zhang *et al.* [5] proposed *pCruise*, in which each taxicab collects the passenger requests from nearby taxicabs and accordingly cruises on the routes with the maximum probability of finding a passenger. Xie *et al.* [8] further proposed *PrivateHunt*, which utilizes a Markov Decision Process to model the appearance of passengers and dispatches taxicabs. However, these methods push the taxicabs to cruise among the locations where passengers are likely to appear, but are not directly applicable for electric taxicabs because they cannot output the optimal decision on where to go and whether to get charged, which minimizes the number of missed passengers for the taxicabs.

III. Metropolitan-Scale Dataset Measurement

A. Dataset Description and Definitions

In this analysis, we use the data recorded from Jan 1, 2015 to Dec 31, 2015 for measurement, which include:

(1) **Taxicab Dataset.** This dataset records the status (e.g., timestamp, GPS position, velocity, occupancy) of 15,610 taxicabs. 6,510 of them are electric taxicabs.

(2) **Charging Station Dataset.** It is also collected by the Shenzhen Transport Committee, which records the information (e.g., GPS position, number of chargers) of 81 existing plug-in charging stations in Shenzhen.

(3) **Road Map.** The road map of Shenzhen is obtained from OpenStreetMap [14]. We use a bounding box with a south-west coordinate ($lat = 22.4450, lon = 113.7130$), and a north-east coordinate ($lat = 22.8844, lon = 114.5270$) to crop the road map data.

We represent the road network of Shenzhen with a directed graph, in which vertices represent landmarks (i.e., intersections or turning points), and edges represent road segments [15], [16], [17]. We introduce the following definition:

Definition 1: Region. The road network is partitioned into a set of $N^G = 496$ regions $G = \{g_0, g_1, \dots, g_{N^G-1}\}$ according to administrative region planning of Shenzhen.

We partition the timeline of a day into 48 30-minute-long time slots. Then, combining the taxicabs' movement records with the changes of their occupancy status, we extracted pick-up position and time (i.e., where and when occupancy status changes from "0" to "1") of each passenger and mapped it to the road network, and calculated the number of passenger pick-ups (i.e., passenger demand) in each region per time slot.

B. Dataset Analysis

1) Suitability of Historical Data for Passenger Demand Inference: Although people's life routines repeat in daily manner, taxicab passenger demand in a time slot (e.g., 08:00-08:30) may vary in different days due to random factors (e.g., weather, ceremony). We notice that the influence of random factors has been reflected in historical passenger demands. Considering that the distribution of passengers can

Fig. 1. A region with 18 buildings.

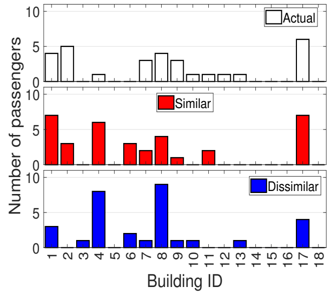

Fig. 2. Comparison of histograms of passengers' building tags.

be represented with the histogram of the buildings where the passengers come from (called the passengers' *building tag*), we believe that the histogram of passengers' building tags can be an effective metric for extracting suitable historical data. Then, we can utilize the suitable historical data to train a passenger demand inference model to infer future passenger demand. By suitable historical data, we mean the previous data in the same time slot (e.g., 13:00-13:30), and under the influence of similar random factors as today. We randomly selected a region with 18 major buildings, which is as shown in Figure 1, and conducted an experiment on inferring the region's passenger demand in different time slots of Mar 5, 2015. The general procedure is: (1) at current time slot of today, we select historical passenger demand data at the same time slot from previous 365 days before Mar 5, 2015 that is under the influence of similar random factors as current time; (2) we utilize the selected suitable historical demand data in the next time slot (i.e., 13:30-14:00) as the predicted demand in the next time slot of today; (3) we repeat this prediction of passenger demand for each time slot throughout today.

For each passenger, we use the building nearest to (in Euclidean distance) his/her pick-up position as his/her building tag. Then we decompose the passenger demand in each time slot into a histogram of building tags, where each column represents a building tag and the corresponding number of passengers. The "Actual" in Figure 2 illustrates an example histogram of region g_i's actual passenger building tags in the time slot 13:00-13:30. Note that each histogram in Figure 2 is generated from the demand data in the time slot 13:00-13:30 of a certain day. We use a vector $\mathbf{h}_i^c$ to represent this histogram (called *building tag histogram vector*), and a vector $\mathbf{h}_i^j$ to represent a histogram of g_i's passenger building tags on j^{th} day. For simplicity, we use $\mathbf{h}^c$ and $\mathbf{h}^j$ for explanation, and we do not show the subscript i unless needed in the following sections. We use the chi-square distance [18] between $\mathbf{h}^j$ and $\mathbf{h}^c$ as their similarity. Specifically, given the building IDs in g_i are $k = 1, 2, \ldots, N^B$, where N^B is the total number of buildings in g_i. Thus, $\mathbf{h}^j$ and $\mathbf{h}^c$ are two $N^B \times 1$ vectors. The chi-square distance between $\mathbf{h}^j$ and $\mathbf{h}^c$ is defined as

$$\chi_j^2 = \frac{1}{2}\sum_{k=1}^{N^B} \frac{(\mathbf{h}_k^j - \mathbf{h}_k^c)^2}{\mathbf{h}_k^j + \mathbf{h}_k^c}. \quad (1)$$

where $\mathbf{h}_k^j$ represents the k^{th} element in vector $\mathbf{h}^j$. The smaller χ_j^2 a previous demand has, the more similar it is to current status. For example, suppose $\mathbf{h}^c$ is composed of 404 passengers from *building1*, 262 passengers from *building2*, and 89 passengers from *building3*. Then $\mathbf{h}^c$ has the following representation: $\{$*building1* (404), *building2* (262), *building3* (89)$\}$. Suppose $\mathbf{h}^1$ has the following representation: $\{$*building1* (201), *building2* (500), *building3* (90)$\}$. The similarity between $\mathbf{h}^c$ and $\mathbf{h}^1$ is $\chi_1^2 = \frac{1}{2} \times (\frac{(404-201)^2}{404+201} + \frac{(262-500)^2}{262+500} + \frac{(89-90)^2}{89+90}) = 71.23$. Suppose $\mathbf{h}^2$ has the following representation: $\{$*building1* (401), *building2* (300), *building3* (100)$\}$. The similarity between $\mathbf{h}^c$ and $\mathbf{h}^2$ is $\chi_2^2 = \frac{1}{2} \times (\frac{(404-401)^2}{404+401} + \frac{(262-300)^2}{262+300} + \frac{(89-100)^2}{89+100}) = 1.61$. Since $\chi_2^2 < \chi_1^2$, $\mathbf{h}^2$ is more similar to $\mathbf{h}^c$.

We conducted an experiment to show the effectiveness of the method on extracting suitable historical demands. In the experiment, we use the historical data that has the most similar histogram (denoted as "Histogram") as the suitable historical data to predict demand value. For example, the "Histogram" in Figure 2 illustrates the histogram of passenger building tags of a historical demand in the time slot 13:00-13:30 that has the most similar histogram to "Actual". Specifically, in the experiment, when inferring each time slot's passenger demand on Mar 5, 2015, we calculate and rank the χ_j^2 of all the previous demand data to select the most suitable historical data that has the minimum χ_j^2. Then, based on the passenger demand of current time slot denoted as the n^{th} time slot (e.g., 13:00-13:30), we use the demand value of "Histogram" in the next time slot denoted as the $(n+1)^{th}$ time slot (e.g., 13:30-14:00) as the predicted demand value in the $(n+1)^{th}$ time slot. Using this way, we predict the passenger demand of each time slot throughout the day. In addition, we also use a randomly selected historical passenger demand in the $(n+1)^{th}$ time slot as the predicted demand value (denoted by "Random"), which serves as the baseline.

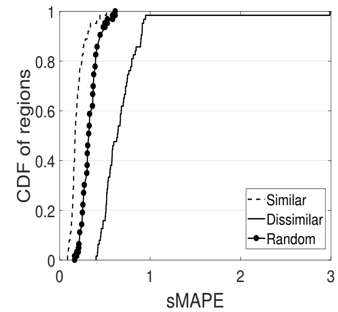

Fig. 3. Distribution of sMAPEs.

We calculated the symmetric Mean Absolute Percentage Error of the inference results (i.e., sMAPE $= \frac{1}{N_s}\sum \frac{|\text{inferred demand}-\text{actual demand}|}{\text{inferred demand}+\text{actual demand}+1}$ [19], [20], where N_s is the number of time slots in a day, and 1 is to avoid division by zero as in [19], [20]) over all time slots for each region. The results are illustrated in Figure 3. We can see that the sMAPEs of the three methods generally follow: "Histogram"<"Random"<"Total". This result confirms that the histogram of passengers' building tags is an effective metric for differentiating the suitability of historical data. The experiment also confirms that the total number of passengers is not a reliable metric for selecting the most suitable historical data for training the inference model. In Section IV-B, we will elaborate how *CD-Guide* extracts suitable historical training data and infer the passenger demand in the next time slot.

2) Variance of Taxicab Passenger Demand: Several previous works [20], [21] have confirmed that taxicab passenger demand in a region has a certain degree of regularity

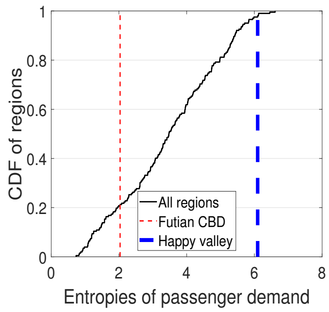

Fig. 4. Distribution of passenger demand entropies.

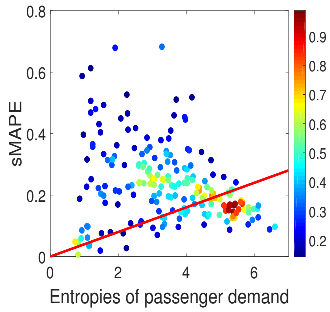

Fig. 5. Scatter plot of passenger demand entropies vs. sMAPE.

(e.g., weekly patterns), but also a certain degree of variance (i.e., fluctuation of demand values due to the influence of random factors), which constrains the maximum predictability of passenger demand in the region (i.e., the maximum accuracy that an inference algorithm can possibly achieve). However, these methods do not explain how the maximum predictability of passenger demand inference can be taken into account in the taxicab charging optimization. Entropy of a time series is effective in measuring the degree of variance (i.e., fluctuation of demand values due to the influence of random factors) of the time series. Generally, the more various the time series is, the larger entropy it will result in, and the less predictable it is. A region g_i's all historical taxicab passenger demands (i.e., passenger demand in each time slot from day 1 to today) can be represented as a time series: $\mathbf{D}_{\text{all}} = \{D_1, \ldots, D_a, \ldots, D_{N_A}\}$, where each element D_a is an observed historical passenger demand in a time slot, and N_A is the total number of collected demand values of g_i since the beginning of observation. Note that D_a can be obtained by summing up all passengers appeared in g_i during the a^{th} time slot. Suppose the time series $\mathbf{D}_{\text{all}} = \{1, 2, 2\}$, then its subsequences are: $\{1\}$, $\{2\}$, $\{2\}$ $\{1{,}2\}$, $\{2{,}2\}$. Its unique subsequences (s_a) are: $\{1\}$, $\{2\}$ $\{1{,}2\}$, $\{2{,}2\}$. Following the definition of human mobility randomness in [21] and [20], the entropy of $\mathbf{D}_{\text{all}}$ is defined as:

$$E = -\sum_{s_a \subset \mathbf{D}_{\text{all}}} \Pr(s_a) \log_2(\Pr(s_a)), \tag{2}$$

where $\Pr(s_a)$ is the probability that a unique subsequence (e.g., $\{1\}$ is a unique subsequence of $\{1, 2, 2\}$) s_a appears in $\mathbf{D}_{\text{all}}$. For example, the probabilities that each unique subsequence of $\mathbf{D}_{\text{all}} = \{1, 2, 2\}$ appears in $\mathbf{D}_{\text{all}}$ are: $\Pr(\{1\}) = \frac{1}{5}$, $\Pr(\{2\}) = \frac{2}{5}$, $\Pr(\{1, 2\}) = \frac{1}{5}$ and $\Pr(\{2, 2\}) = \frac{1}{5}$. The entropy of $\mathbf{D}_{\text{all}}$ is calculated as $\frac{1}{5}\log_2 5 + \frac{2}{5}\log_2 \frac{5}{2} + \frac{1}{5}\log_2 5 + \frac{1}{5}\log_2 5 = 1.92$. The fewer unique subsequences $\mathbf{D}_{\text{all}}$ has (i.e., lower similarity of historical passenger demand values), the smaller E will be.

We calculated the entropy of passenger demand time series (including all observed passenger demand values from Jan 1 to Dec 31, 2015) for each region by Equation (2). Figure 4 shows the CDF of the results. We can see that 80% of the regions have a passenger demand entropy higher than 2.03 (red dashed line), which means that the passenger demand in these regions has a higher degree of variance than Futian CBD. We need to use the entropy of passenger demand to measure the different degrees of variance for the regions.

Recall that in Section III-B1, we have obtained the sMAPEs of the passenger demand inference result of "Similar" throughout all time slots of Mar 5, 2015 for all regions. To analyze the relation between the inference accuracy and the passenger demand entropy of the regions, we further drew a density scatter heat plot between the entropies of passenger demand and the sMAPEs of all regions, as shown in Figure 5. Each point represents a region. The warmer color a point has, the more concentrated it is with the other points, which have similar entropies of passenger demand and sMAPEs. We also drew a line across the points. We can see that most points are scattered around the line, which means that for the regions with a larger entropy, their inference error will be higher (i.e., lower inference accuracy) and vice versa. This result indicates that the maximum predicability of passenger demand in a region is dependent on the randomness of the region's historical passenger demand time series. The maximum predicability constrains the maximum accuracy of the region's passenger demand inference result. In Section IV-B3 and Section IV-C, we will introduce how *CD-Guide* determines the maximum predictability of the inference result and considers it in taxicab dispatching and charging optimization.

IV. System Design of CD-Guide

A. Framework of CD-Guide

CD-Guide consists of the following three stages:

1. Map gridding & information derivation. First, the entire city area is partitioned into a *Gridded Roadmap*. Also, the taxicab dataset is cleaned up (e.g., filtering out positions out of the actual range of Shenzhen, redundant positions). Then, based on the cleaned data, we derive the *Passenger Demand Records* of taxicabs in each region.

2. Taxicab passenger demand inference (Section IV-B). Based on the output *Passenger Demand Records* from the first stage, we extract *Suitable Historical Data* that are under the influence of random factors similar as current time for each region. Then, we apply *Inference Model of Taxicab Passenger Demand* to infer demand value in the next time slot. Finally, we calculate the *Maximum Predictability of Taxicab Passenger Demand* for more accurate inference of passenger demand.

3. Optimization of taxicab dispatching and charging (Section IV-C). For each taxicab, we first use its SoC and taxicab passenger demands in each region for the *Determination of Taxicab Service Ability* for each region. A taxicab's service ability in a region is defined as the ratio of passenger trips in a region after it arrives at the region until the end of the next time slot that its SoC can support. Then we develop a *Reinforcement Learning based Taxicab Dispatching and Charging* method to decide which region the taxicab should drive to and whether to get charged in the region.

B. Taxicab Passenger Demand Inference

In the following, we explain how the taxicab passenger demand in a region g_i is inferred. Since the inference process is achieved per region, we do not show the subscript i for simplicity. We firstly introduce how *CD-Guide* utilizes the distribution of passengers' building tags to select the historical passenger demands that are suitable for training the model for inferring the taxicab passenger demand in the next time slot. Then, we design an linear regression based model to infer the taxicab passenger demand in the next time slot. Finally, we elaborate how *CD-Guide* calculates the maximum predictability of passenger demand for more accurate inference of passenger demand value.

1) Extracting Suitable Historical Data: The analysis result in Section III-B1 has demonstrated that the historical passenger demand with a total number of passengers approximate to current passenger demand is not guaranteed to be suitable for training the inference model. Specifically, given the building tag histogram vector of region g_i in current time slot (i.e., n^{th} time slot) of today ($\mathbf{h}^c(n)$), we first use Equation (1) to calculate its similarity (i.e., chi-square distance) to the historical building tag histogram vector of region g_i in the same time slot ($\mathbf{h}^j(n)$) of each day in the previous N^D days (e.g., 365 days). Then, we rank the historical passenger demands in previous N^D days by increasing order of their chi-square distance to $\mathbf{h}^c(n)$, and select the top ranked β (e.g., 10%) days' passenger demands as training data. Finally, we obtain a sequence of N^d suitable previous passenger demands during n^{th} time slot from the total N^D historical passenger demands: $\{D^j(n)|j = 1, 2, \ldots, N^d\}$, where $D^j(n)$ represents the taxicab passenger demand in region g_i during n^{th} time slot on j^{th} day, and N^d is the number of days of the extracted suitable passenger demands. A larger N^D and β will increase the training computation overhead but may include the influence of more random factors that are similar as current time in the extracted suitable historical training data. To find the best values for them, we vary each variable within a certain range (e.g., [30, 60] for N^D and [5%, 15%] for β). We try different combinations of the N^D and β values, and choose the combination that achieves the minimum chi-square distance to $\mathbf{h}^c(n)$ as the final values of N^D and β. In implementation, we determine these parameters offline.

2) Inference Model of Taxicab Passenger Demand: We want the inference model to utilize the extracted suitable historical data (i.e., $\{D^j(n)|j = 1, 2, \ldots, N^d\}$) to infer passenger demand in the next time slot of today (i.e., $D^c(n + 1)$). The analysis results in Section III-B1 have demonstrated that for the historical passenger demand with a building tag histogram similar to that of current passenger demand, their trend of passenger demand in the next time slot will also be similar. Thus, if the training output in current time slot is close to current passenger demand (i.e., $D^c(n)$), we can use this model to estimate the demand value in the next time slot (i.e., $D^c(n + 1)$) with a high accuracy. Therefore, we propose a taxicab passenger demand inference model based on the linear regression of the extracted historical demand data.

The general procedures of training the inference model consists of: (1) we first input $\{D^j(n)|j = 1, 2, \ldots, N^d\}$ as the training data to the inference model, and learn the parameters of the inference model to minimize the error between the training output and current passenger demand $D^c(n)$. Once the best parameters are determined, the training of the inference model is complete. (2) Then we input the suitable historical data in $(n+1)^{th}$ time slot (i.e., $\{D^j(n+1)|j = 1, 2, \ldots, N^d\}$) to the inference model to infer the passenger demand in $(n + 1)^{th}$ time slot of today (i.e., $D^c(n + 1)$).

Considering that $D^j(n)$ is actually the sum of passenger demand contributed by each building $k \in g_i$, we use its corresponding building tag histogram vector $\mathbf{h}^j(n)$ to represent $D^j(n)$. Let $H(n)$ be a $N^B \times N^d$ matrix with each column representing the building tag histogram vector of an extracted suitable historical passenger demand in n^{th} time slot. That is, $H(n) = [\mathbf{h}^1(n), \mathbf{h}^2(n), \ldots, \mathbf{h}^{N^d}(n)]$. Note that N^B is the total number of buildings in g_i. Let $\mathbf{w}$ be a $N^d \times 1$ weight vector of the N^d days' extracted suitable passenger demands. As a result, a $N^B \times 1$ vector $H(n)\mathbf{w}$ is the model's training output for $\mathbf{h}^c(n)$, which is the building tag histogram vector on today in n^{th} time slot (i.e., ground truth). Thus, the key objective for training the inference model is to find an optimal $\mathbf{w}$ that minimizes the error between $\mathbf{h}^c(n)$ and $H(n)\mathbf{w}$:

$$\mathbf{w}^* = \underset{\mathbf{w}}{\operatorname{argmin}}(\mathbf{h}^c(n) - H(n)\mathbf{w})'(\mathbf{h}^c(n) - H(n)\mathbf{w}), \quad (3)$$

where $()'$ means matrix transpose, and $\mathbf{w}^*$ is the optimal solution, which can be obtained by least-square fitting [22]. Finally, the building tag histogram vector of g_i during the next time slot $t + 1$ is

$$\mathbf{h}^c(n + 1) = H(n + 1)\mathbf{w}^*. \quad (4)$$

The inferred total taxicab passenger demand in g_i during the next time slot of today (i.e., $D^c(n + 1)$) is obtained by summing the elements in $\mathbf{h}^c(n + 1)$.

3) Maximum Predictability of Taxicab Passenger Demand: The data analysis results in Section III-B2 have illustrated that the maximum predictability of a region's future passenger demand value is dependent on the randomness (entropy) of the region's historical passenger demand time series, and measures how reliable the passenger demand inference result is. One question is: how to determine the maximum predictability of the passenger demand for each region and consider it in the optimization of electric taxicab dispatching and charging? In this section, we elaborate how the maximum predictability of the region's passenger demand value is determined.

We first compute the entropy of historical passenger demand time series E by Equation (2) for each region offline to save real-time computation overhead. Suppose the number of unique taxicab passenger demand values in $\mathbf{D}_{\text{all}}$ is N^u. For example, for $\mathbf{D}_{\text{all}} = \{1, 2, 2\}$, $\mathbf{D}_{\text{all}}$ only has $N^u = 2$ unique demand values: 1 and 2. That is, N^u is the number of possible values that a future taxicab passenger demand (e.g., $D^c(n+1)$) can have. Among the N^u demand values, only one value is correct. Suppose the probability that we can accurately infer the demand value of $D^c(n + 1)$ is $P^{\max}$ (i.e., the maximum predictability of a future passenger demand value in g_i). Thus, the probability that we will inaccurately infer the demand value is $1-P^{\max}$ [20], [21]. According to [20], [21], we assume the probability of inferring the remaining inaccurate $N^u - 1$ possible demand values follows a uniform distribution. That is, the probability of inaccurately inferring any one of the other

N^u-1 possible values is $\frac{1-P^{\max}}{N^u-1}$, then E can be also calculated as the entropy resulted from accurate case and inaccurate case:

$$\begin{aligned} E &= -P^{\max}\log_2(P^{\max}) - \sum_{N^u-1}\frac{1-P^{\max}}{N^u-1}\log_2(\frac{1-P^{\max}}{N^u-1}) \\ &= -P^{\max}\log_2(P^{\max}) - (1-P^{\max})\log_2(1-P^{\max}) \\ &+ (1-P^{\max})\log_2(N^u-1). \end{aligned} \tag{5}$$

Since E is known, and N^u can be determined from $\mathbf{D}_{\text{all}}$, thus $P^{\max}$ can be obtained by solving Equation (5). Finally, the maximum predictability of the passenger demand value $D^c(n+1)$ is determined as $1-P^{\max}$. Since we expect to dispatch the taxicab to the region with a relatively higher predictability of passenger demand (i.e., higher inference accuracy, $1-P_i^{\max}$ should be as low as possible), we adjust the passenger demand value $D^c(n+1)$ to be $\widetilde{D}^c(n+1) = \frac{D^c(n+1)}{1-P_i^{\max}}$ in later optimization of taxicab dispatching and charging.

4) Determination of Taxicab Service Ability: When dispatching a taxicab to pick up its next passenger, we expect that the taxicab has enough SoC to support the trip of its next passenger. This is because that the trip length of the passenger determines the energy consumption of the taxicab. Intuitively, the trip lengths of civilians in a city are relatively stable during the same time slot among different days due to life routines. Therefore, from the suitable historical data of a region g_i extracted from Section IV-B1 (i.e., $\{D_i^j(n)|j=1,2,\ldots,N_i^d\}$), we collect the distribution of possible passenger trip lengths at specific time (e.g., 13:10) in the next time slot in previous days, and use it as an estimation of the distribution of passenger trip lengths in the next time slot of today. We collect this distribution for each region g_i, and calculate the taxicab's service ability in g_i (i.e., ratio of future passenger trips that a taxicab's current SoC can support). Specifically, suppose current SoC of a taxicab is SoC, and the lower bound of a taxicab's SoC is $SoC_{\min}$ (e.g., 20%), which is set to ensure that the taxicab will have enough remaining SoC to go to the nearest charging position upon the exhaustion of its battery. The taxicab's service ability during specific time duration within a time slot (e.g., [13:10, 13:20] within time slot 13:00-13:30) in g_i is calculated as:

$$\Phi_i(SoC|[t_s,t_e]) = \Pr\{SoC - c_e(l_i^d + l_i^p) > SoC_{\min}|t_s \leqslant t_i^p \leqslant t_e\}, \tag{6}$$

where c_e is the energy consumption rate (i.e., the amount of SoC consumed by unit length of driving) of the taxicab, l_i^d is the driving distance from the taxicab's current position to the nearest position in region g_i, and l_i^p is the trip length of a passenger in region g_i. Therefore, $SoC - c_e(l_i^d + l_i^p)$ is the remaining SoC after the taxicab arrives at g_i. t_i^p is the appearance time of a passenger in g_i, t_s is the start time of the time duration, t_e is the end time of the time duration. Equation (6) can be equivalently transformed into the following form:

$$\Phi_i(SoC|[t_s,t_e]) = \Pr(l_i^p < \frac{SoC - SoC_{\min} - c_e l_i^d}{c_e}|t_s \leqslant t_i^p \leqslant t_e), \tag{7}$$

which means that based on the current SoC of the taxicab SoC, the taxicab can support passenger trip lengths shorter than $\frac{SoC-SoC_{\min}-c_e l_i^d}{c_e}$ during specific time duration $[t_s,t_e]$. Recall that we assume the maximum pool of passengers that the taxicab can possibly pick up in region g_i consists of passengers that will appear in the region within n^{th} and $(n+1)^{th}$ time slots. That is, the actual pool of passengers that the taxicab can support with its current SoC during a specific time duration $[t_s,t_e]$ (e.g., the taxicab's charging time duration) is $\Phi_i(SoC|[t_s,t_e])(\widetilde{D}_i^c(n)+\widetilde{D}_i^c(n+1))$. From the estimated distribution of future passenger trip lengths, we can calculate Φ_i for each region g_i during specific time duration for a taxicab. Then we extract the regions that have $\Phi_i > 0$ and define them as the set of candidate regions for dispatching the given taxicab:

$$\widetilde{G} = \{g_i \in G | \Phi_i > 0\}, \tag{8}$$

which means that the taxicab can afford the trip length of at least one passenger in these regions. Recall that the taxicab's total number of potential passengers in each candidate region of $\widetilde{G}$ is weighted by the taxicab's service ability (i.e., $\Phi_i(SoC|[t_s,t_e])(\widetilde{D}_i^c(n)+\widetilde{D}_i^c(n+1))$).

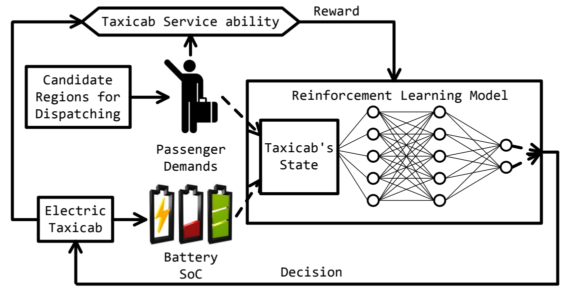

Fig. 6. Training of reinforcement learning model.

C. Reinforcement Learning based Taxicab Dispatching and Charging

We use the RL model to generate the action. Specifically, the RL mode produces policy $\pi: s_n \mapsto a_n$, that is, given state s_n, it outputs a_n as the optimal action that maximize the reward. We define *reward* as the number of potential passengers that the taxicab can pick up. We utilize the taxicab's SoC and the predicted passenger demands of the candidate regions ($\widetilde{G}$) in the n^{th} and $(n+1)^{th}$ time slots (i.e., $\{\widetilde{D}_i^c(n)+\widetilde{D}_i^c(n+1)|g_i \in \widetilde{G}\}$) to describe the state s_n. That is, $s_n = (SoC, \{\widetilde{D}_i^c(n) + \widetilde{D}_i^c(n+1)|g_i \in \widetilde{G}\})$. As shown in Figure 6, the state is the input to the reinforcement learning model. The output of the model is an action (a_n), i.e., the decision for dispatching and charging in the n^{th} time slot including: 1) which region the taxicab should drive to (denoted by $x_i \in \{0,1\}$); 2) whether the taxicab should get charged in the region (denoted by $y_i \in \{0,1\}$). That is, $a_n = (x_i, y_i)$. Specifically, if $x_i = 1$, the taxicab is dispatched to g_i; if $x_i = 0$, the taxicab will not drive to g_i. If $y_i = 1$, the taxicab will receive a recharge in g_i when it arrives at g_i; if $y_i = 0$, the taxicab will not receive a recharge in g_i.

We use the number of potential passengers that the taxicab can pick up by taking an action as the reward for the Reinforcement Learning (RL) model. If $x_i = 1$ and $y_i = 1$ (i.e., the taxicab will drive to g_i and receive a recharge in g_i), the taxicab will spend τ_i^d on driving to g_i, and τ_i^c on receiving a full recharge in g_i based on its current SoC. Thus, starting from current time t_0, the time duration that the taxicab can pick up passengers in the n^{th} and $(n+1)^{th}$ time slots is $[t_0+\tau_i^d+\tau_i^c, t_0+2T]$, where T is the duration of a time slot. $[t_0+\tau_i^d+\tau_i^c, t_0+2T]$ is defined as the time duration from the taxicab's completion of charging in region g_i until the end of the n^{th} and $(n+1)^{th}$ time slots. Similarly, if $x_i = 1$ but $y_i = 0$ (i.e., the taxicab will drive to g_i but will not receive a recharge in g_i), the time duration that the taxicab can pick up passengers in the n^{th} and $(n+1)^{th}$ time slots is $[t_0+\tau_i^d, t_0+2T]$. The taxicab's reward function resulted by x_i and y_i can be represented as:

$$\begin{aligned} r(s_n, a_n, s_{n+1}) &= (\Phi_i(1|[t_0+\tau_i^d+\tau_i^c, t_0+2T])y_i \\ &+ \Phi_i(SoC|[t_0+\tau_i^d, t_0+2T])(1 \\ &- y_i))(\widetilde{D}_i^c(n)+\widetilde{D}_i^c(n+1))x_i, \end{aligned} \tag{9}$$

where $\Phi_i(1|[t_0+\tau_i^d+\tau_i^c, t_0+2T])$ is the taxicab's service ability in g_i after charging. The reason $SoC = 1$ is that the taxicab will firstly fully recharge its battery and then drive to pick up a passenger. $\Phi_i(SoC|[t_0+\tau_i^d, t_0+2T])$ is the taxicab's service ability in g_i without charging. Both $\Phi_i(1|[t_0+\tau_i^d+\tau_i^c, t_0+2T])$ and $\Phi_i(SoC|[t_0+\tau_i^d, t_0+2T])$ are obtained from historical passenger demands.

We use the Deep Neural Network (DNN) to obtain the optimal policy as in [23]. The optimal policy π^* is defined as one map $\pi^*: s_n \mapsto a_n$ that maximizes the reward received by taking the correspoinding action a_n given state s_n. To discover the optimal dispatching and charging policy that maximizes the reward under various states, we utilize the long-term historical passenger demands (e.g., passenger demands in previous 365 days) for offline training of the reinforcement learning model. Once the training is complete, the taxicab can utilize the optimal policy to generate the dispatching and charging action in real time. During the training process, the inputs are the state, the different actions the taxicab takes (i.e., driving to each region and choose to get recharged or not) and the reward calculated by Equation (9). Specifically, we suppose that the taxicab's initial state starts from a randomly selected region with $SoC = 1$. Then, we simulate the movement of the taxicab from one region to another region. That is, the taxicab transfers from one state to another state by taking different actions. Finally, we utilize the historical passenger demand value information at each time when the taxicab takes an action to calculate the reward. The RL model calculates the Q value of a series of successive actions as the sum of the rewards resulted from the actions. Reinforcement learning finds a policy that is optimal in the sense that it maximizes the expected value of the total reward over all the series of successive actions.

V. Performance Evaluation

A. Comparison Methods

To evaluate *CD-Guide*'s performance, we compare its taxicab passenger demand inference performance with a representative method that utilizes Bilinear Poisson regression model to consider the effects of random factors on passenger demand values (*BilinearPoisson* in short) [4], and the method introduced in Section III-B1 (*Similar* in short). Specifically, throughout all the time slots in a day, *Similar* utilizes the historical demand value, of which histogram of passenger building tags has the smallest χ_j^2 to that of current passenger demand value, as the predicted passenger demand in the next time slot. *BilinearPoisson* develops a bilinear Poisson regression model, which takes all the historical demands as input training data without selection. It uses random factors including day of week, holidays and weather as inputs to the model and learn their effects on passenger demand.

We also compare the performance of *CD-Guide* in serving passenger requests with a representative taxicab dispatching method (*PrivateHunt* in short) [8], and a baseline method that randomly dispatches the taxicab to a nearby region (*Baseline* in short). *PrivateHunt* utilizes the future passenger demand inferred from historical passenger demands to determine the cruising policy for each taxicab, in order to maximize the taxicab's likelihood of picking up passengers. For fairness, we use the passenger demand inference result output by *CD-Guide*. Then, it utilizes a Markov Decision Process to model the appearance of passengers and uses the probability of passenger appearance to calculate the probability of picking up a passenger in each region. Finally, it recommends the region that has the maximum probability of picking up a passenger to the taxicab. The distribution of chargers follows the existing charging stations in Shenzhen. Since *PrivateHunt* and *Baseline* do not have specific methods to optimize the charging of taxicabs, we set that the taxicabs in these two methods will drive to the nearest charger for charging whenever their SoC is below a threshold (20% in experiment).

B. Experiment Settings

We suppose that every electric taxicab starts driving with full energy in battery at the beginning of a day. The battery capacities of the taxicabs follow a uniform distribution from 65 kWh to 85 kWh, which is the common battery capacity of electric taxicabs in Shenzhen [11]. The charging rate of a charging infrastructure is set to 150 kW [24]. The energy consumption rate of a taxicab is a 0.425 kWh/km [10], [11]. The SoC lower bound $SoC_{\min}$ is set to 20%. We use the historical data from July, 2014 to June, 2015 as the training data for *CD-Guide*, *Similar* and *BilinearPoisson*. The random factors such as day of week and holidays are obtained from Shenzhen's calendar of 2015, and the weather data is obtained from the China Meteorological Data Service Center [25]. All 16 weather types (e.g., Sunny, Rainy) are denoted with one hot coding (i.e., if a day is sunny, its code is 1, or 0 otherwise). We aim to infer the passenger demand in each time slot of July 15, 2015 to compare the accuracy of different passenger demand inference methods. The values of parameters related to training (i.e., N^D, β) are $N^D = 365$ and $\beta = 10\%$. Based on the deployment of existing charging stations in Shenzhen, we use SUMO [26] to simulate the operation of 1,000 EVs on Shenzhen's road network for 24 hours. We

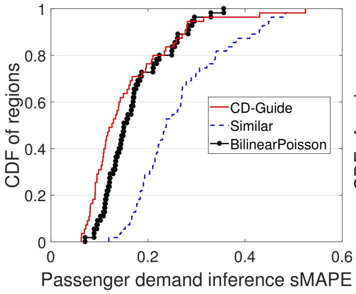

Fig. 7. Distribution of passenger demand inference sMAPEs.

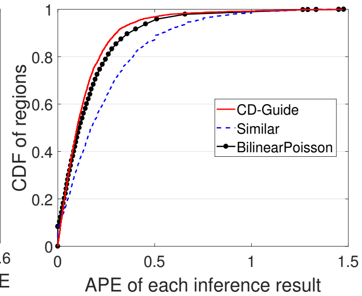

Fig. 8. Distribution of the APEs of all inference results.

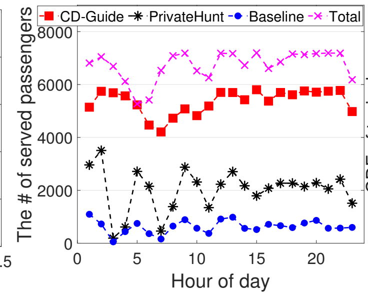

Fig. 9. The number of served passengers of all taxicabs.

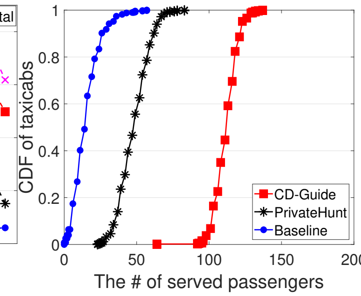

Fig. 10. Distribution of the numbers of taxicabs' served passengers.

converted OpenStreetMap road network of Shenzhen to a SUMO road network file. In SUMO, we let taxicabs drive by the dispatching strategy of each comparison method.

The metrics we measured are:

- *Passenger demand inference sMAPE*. For each region, we measure the sMAPE over all time slots throughout a day for each region, and collect the CDF of the sMAPEs of all the regions. We also collect the CDF of the Absolute Percentage Error (APE) [19], [20] (i.e., APE $= \frac{|\text{inferred demand} - \text{actual demand}|}{\text{inferred demand+actual demand+1}}$) of the inference result in each time slot of all the regions. The purpose of this metric is to compare the inference accuracy of different passenger demand inference methods.
- *The number of served passengers*. We measure the number of passengers served by all taxicabs in all time slots throughout a day. We also measure the number of passengers served by each taxicab, and collect the CDF of all the served passengers. The purpose of this metric is to compare the performance of different taxicab dispatching methods in serving passengers.

C. Experimental Results

1) Passenger demand inference sMAPE: Figure 7 shows the distribution of the sMAPEs of taxicab passenger demand inference results in all regions. Figure 8 shows the distribution of the APEs of the inference results in each time slot of all regions. We can see that for most regions (>90%), the sMAPEs follow: *CD-Guide*<*BilinearPoisson*<*Similar*. While for the other regions (<10%), the sMAPEs follow: *CD-Guide*≈*BilinearPoisson*<*Similar*. The APEs of the inference results generally follow *CD-Guide*⩽*BilinearPoisson*<*Similar*.

Similar results in the highest average sMAPE over all regions. This is because that it uses only one suitable historical passenger demand value, of which histogram of passenger building tags has the smallest χ_j^2 to that of current passenger demand value, as the demand value in the next time slot. Although the historical data is a good indicator of the changing trend of passenger demand in the next time slot, simply using a historical passenger demand value as a future demand value will inevitably cause a high inference error, because one suitable historical data sometimes cannot catch the influence of all random factors.

In comparison, *BilinearPoisson* has a much lower sMAPE in all regions. This is because that *BilinearPoisson* regresses the change of passenger demand value by time via the bilinear Poisson regression model. After training the time-variant Poisson parameter with large-scale historical data, it has taken into account the long-term temporal change pattern of taxicab passengers. In addition, after adding the quantified effect of random factors to the bilinear Poisson regression model, *BilinearPoisson* can better adjust its inference result against unexpected cases (e.g., day of the week, weather) that are not reflected in historical data. However, its inference accuracy is constrained by the maximum predictability of future passenger demand in some regions. This is why the sMAPEs of *BilinearPoisson* in around 75% of the regions are similar or lower than those in *CD-Guide*.

Compared with *BilinearPoisson*, *CD-Guide* achieves a lower sMAPE in around 75% of the regions, a similar sMAPE in around 20% of the regions, and a slightly higher sMAPE in the rest 5% of the regions. This is because that in *CD-Guide*, the suitable historical data extraction process has ensured that the training data for inference have been limited to previous days that have similar histograms of passenger tags, which means that they are under the influence of similar random factors. For most regions (i.e., 95%) with a relatively higher passenger demand predictability, the extracted suitable historical data has covered sufficient random factors that may influence the region's future passenger demand. What's more, *CD-Guide* utilizes the linear regression to learn the weights of the random factors in generating the inference result. As a result, the inference accuracies of passenger demands in the 95% regions are sufficiently high. For the rest 5% regions, which have relatively lower predictability, their future passenger demand does not have much commonness with their historical demands (i.e., unpredictable), catching the overall random factors that affect the historical demands does not help improve the predictability of passenger demand (i.e., unpredictable). As a result, *BilinearPoisson* achieves a lower sMAPE due to its learned influence of several random factors. This experiment result demonstrates that *CD-Guide*'s passenger demand inference method is effective in approximating the actual passenger demand with a higher accuracy, and its effectiveness differs in the regions due to the different predictability of passenger demand in the regions.

2) The Number of Served Passengers: Figure 9 shows the number of passengers served by all the taxicabs and the actual total number of passengers in each hour of a day under different taxicab dispatching methods. Figure 10 shows the CDF of the numbers of served passengers of all the taxicabs under different methods. We can see that in both figures, the results follow: *Total*>*CD-Guide*>*PrivateHunt*>*Baseline*.

In Figure 9, *Baseline* always achieves the minimum total number of served passengers during all hours in a day. This is because that it simply dispatches the taxicab to a nearby region without considering the passenger demand in the region. So the taxicab cannot efficiently discover passengers when driving. From Figure 10, we can see that almost all taxicabs cannot pick up more than 50 passengers in a day.

In comparison, the taxicabs of *PrivateHunt* picked up much more passengers than those in *Baseline*. This is primarily because that *PrivateHunt* employs a Markov Decision Process to determine the probability of picking up a passenger and the possible duration of cruising time without a passenger onboard. The dispatched taxicab is able to quickly discover a passenger by following the recommended route.

The taxicabs of *CD-Guide* achieve the highest and the second highest total number of served passengers during all hours in a day, respectively. We can see that the curve of *CD-Guide* generally changes accordingly with the change of the total number of passengers. This observation verifies that the service of the taxicabs of *CD-Guide* was not greatly effected by their charging time. This is because that *CD-Guide* takes into account the effect of charging time on the number of potential passengers, and meanwhile ensure that the taxicab has sufficient SoC throughout a day.

VI. Conclusion

Accurate inference of future passenger demand and avoidance of missing too many passengers caused by battery charging is essential for efficient dispatching of electric taxicabs. Our proposed *CD-Guide* is the first electric taxicab *C*harging and *D*ispatching approach that *Guide*s electric taxicabs to minimize their number of missed passengers due to charging. Our analytical results on a metropolitan-scale electric taxicab passenger demand dataset provide insights for the design of *CD-Guide*. We utilize the histogram of passengers' building tags to extract suitable historical passenger demands for training a linear regression based passenger demand inference model, and adjust the inference result considering the maximum predictability of taxicab passenger demand in each region. We design a optimization problem based model that guides a taxicab to receive charging with minimized number of missed passengers, maximized probability of picking up a passenger and sufficient SoC during the rest time slots of a day. We conducted trace-driven experiments on SUMO to verify the performance of *CD-Guide*. Compared with previous methods, *CD-Guide* increases the number of served passengers by 100% on average, and maintains the average SoC of all taxicabs above 80% during all time slots.

Acknowledgements

This research was supported in part by U.S. NSF grants NSF-1827674, CCF-1822965, OAC-1724845, Microsoft Research Faculty Fellowship 8300751, The Science and Technology Development Fund, Macau SAR (File no. 0015/2019/AKP).

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