

ForETaxi: Data-Driven Fleet-Oriented Charging Resource Allocation in Large-Scale Electric Taxi Networks

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Charging processes are the key to promoting electric taxis and improving their operational efficiency due to frequent charging activities and long charging time. Nevertheless, optimizing charging resource allocation in real time is extremely challenging because of uneven charging demand/supply distributions, heuristic-based charging behaviors of drivers, and city-scale of the fleets. The existing solutions have utilized real-time contextual information for charging recommendation, but they do not consider the much-richer fleet information, leading to the suboptimal individual-based charging recommendation. In this paper, we design a data-driven fleet-oriented charging recommendation system for charging resource allocation called ForETaxi for electric taxis, which aims to minimize the overall charging overhead for the entire fleet, instead of individual vehicles. ForETaxi considers not only current charging requests but also possible charging requests of other nearby electric taxis in the near future by inferring their status in real time. More importantly, we implement ForETaxi with multiple types of sensor data from the Chinese Shenzhen city including GPS data, and taxi transaction data from more than 13,000 electric taxis, combined with road network data and charging station data. The data-driven evaluation results show that compared to the state-of-the-art individual-based recommendation methods, our fleet-oriented ForETaxi outperforms them by 16% in the total charging time reduction and 82% in the queuing time reduction.

CCS Concepts: • Networks \rightarrow Cyber-physical networks; • Human-centered computing \rightarrow Empirical studies in ubiquitous and mobile computing;

Additional Key Words and Phrases: Electric taxi, data-driven, fleet-oriented, charging recommendation, resource allocation

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1 INTRODUCTION

With more and more advanced sensing and communication devices deployed on vehicles, ubiquitous sensor data (e.g., GPS and transaction data) are available, which provide us great opportunities to enhance their mobility and energy performance. As an important mode of urban mobility, taxis are essential for people's daily activities [45]. Taxis typically have high gas consumption and emissions due to their long-time daily operation, e.g., 24-7, around-the-clock, which undoubtedly brings great challenges to the sustainable development of cities [49]. Compared to the conventional gas taxis, the **electric taxis (ETs)** show considerable advantages in terms of gas consumption and emissions, e.g., zero tailpipe emissions, which motivate many city governments to implement full ET networks, e.g., Beijing, Shenzhen, and New York City [27]. For example, all taxis in Shenzhen have been replaced with electric vehicles and New York City also has the initiative to replace one-third of its taxis with ETs by the end of 2021 [7].

Despite the obvious advantages of oil energy-saving and environmental protection, ETs have not been adopted worldwide due to several reasons e.g., low cruising miles, high prices, and most importantly, complicated charging problems. Among these issues, charging is the key concern that hinders the ETs to achieve their full potential [16, 32, 39]. In particular, ET charging is extremely challenging due to unbalanced charging demand and supply. (i) Demand: because of limited battery capacity, ETs have a low endurance mileage (also called cruising mileage) and need several times charging in a day due to their long daily mileage, and each charging usually lasts for half an hour to two hours. For example, based on our analysis, even though ETs in Shenzhen have a maximum cruising mileage of 300km, the actual mileage is much lower due to traffic congestion, environmental factors, and human factors [30]. On summer nights, the average daily mileage is around 220km due to air conditioning and headlights. Given their operating nature, almost all ETs charge during the non-rush hours and shift time, which leads to the high yet concentrated charging demand [25]. (ii) Supply: because of high cost and security concerns, the number of charging stations in urban downtown areas is limited, and fast charging points in each station are also insufficient, which leads to the prolonged and unforeseeable waiting time at stations. [36]. A combination of charging demand and supply issues makes the current charging strategy rather heuristic, i.e., most ET drivers only choose the nearest charging stations they know to charge their ETs during the non-rush hour or shift time, which makes the charging issue even worse.

To address the complicated charging issue, many researchers have focused on different aspects of this topic due to its importance, e.g., individual charging recommendation [25], charging station deployment [13], electric vehicle charging scheduling via park-and-charge [15], and charging time planning [4]. However, most charging recommendation systems are focused on individual vehicle recommendations and have not considered the uncertain waiting time and charging service time due to lack of real-world data. More importantly, they did not consider this issue from a fleet perspective, which results in the underutilized fleet information and fail to collectively infer the current and future status of the ET fleet for a global charging optimization. Therefore, it motivates us to design a fleet-oriented charging recommendation system to achieve global charging optimization for ET fleets with real-time charging resource allocation.

However, charging recommendation is more challenging by considering the fleet information, e.g., later possible charging requests by ETs and service time of ETs. Fortunately, as one of the initial pilot cities to promote ETs, the real-world data collected from diverse sensors in Shenzhen make it possible for us to conduct research on the data-driven fleet-oriented charging modeling and resultant recommendation based on large-scale data. In this paper, we argue that the data-driven fleet-oriented charging recommendation is a promising solution to solve the ETs charging problem. This is because, in addition to the status of a particular ET, we also utilize the real-time status of the entire ET fleet, which provides more comprehensive information to infer the various status of ETs and charging stations, e.g., the queuing time at charging stations, charging service time, and the potential future charging requests, which has not been fully considered by current individual-based recommendations. Specifically, the key contributions of this paper are as follows:

- We conduct a comprehensive investigation to study the fleet-oriented charging modeling and related recommendation with real-world sensor data of more than 13,000 ETs. Such a large-scale study has the potential to advance our understanding on ET operating patterns and resultant charging recommendations. It enables us to find real-world charging issues, which are hard to be discovered by other simulation-based or small-scale studies.
- We design a fleet-oriented recommendation system called ForETaxi to minimize the overall charging time of the entire fleet, instead of an individual ET based on historical and real-time multi-source data. ForETaxi considers detailed fine-grained charging and recommendation activities by inferring the battery status, queuing time, and service time of ETs, as well as the charging demand and passenger demand in the near future. We only leverage existing charging infrastructure to reduce the overall charging time for the ET fleet, which does not involve high costs for building new charging stations.
- More importantly, we extensively implement and evaluate ForETaxi based on real-world sensor data in Shenzhen including GPS records and transaction records from more than 13,000 ETs, as well as all ET-exclusive charging stations in 2018. The results show that compared with individual-oriented recommendations, ForETaxi reduces 82% of the queuing time and 16% of total charging time, respectively.

2 RELATED WORK

In this section, four categories of related works are reviewed including charging station deployment, electric vehicle charging, gas vehicle refueling, and resource allocation.

2.1 Charging Station Deployment

The objective of charging station deployment [9, 16, 18, 28] is to find the optimal locations to deploy charging stations and optimally assign charging points to each station. With the rapid promotion of electric vehicles, deploying more new charging stations becomes the most direct approach to facilitate the charging of electric vehicles for reducing the queuing time, so there is much electric vehicles related research in this direction. Li et al. [16] developed a charging station deployment and charging point placement framework (i.e., its main contribution) to minimize the overall charging time. Wahl et al. [28] designed a novel Deep Reinforcement Learning approach to solve the charging station placement problem. Du et al. [9] studied the EV charging station planning problem for deploying charging infrastructure (locations of stations and numbers of chargers per station) to maximize the satisfied charging demand. However, enough charging stations cannot guarantee there is an available charging point in a specific station for an EV. In addition, the cost for deploying new charging stations is very expensive, especially for some large cities like

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New York City, London, and Beijing, where the land resources are limited for large charging stations, so charging recommendation is an orthogonal effort of charging station deployment.

2.2 Electric Vehicle Charging

Electric Vehicle Charging became a popular research topic in recent years with the increasing promotion of EVs [11, 25, 29, 34, 38]. The objective of charging recommendation is to recommend each vehicle to a charging station for some benefits, e.g., shortest time spent, lowest money cost, but almost all of them focus on the individual recommendation. Different from scheduling, which refers to when and whether to charge in a mandatory fashion [31, 35], charging recommendation is focused on recommending where and which charging station to charge [5]. Fan et al. [10] considered both order dispatch and charging for electric self-driving taxi systems to maximize long-term cumulative profit of ride-hailing platforms. Wang et al. [33] designed a system called Record to jointly optimize repositioning and charging for shared EVs with dynamic deadlines. Schoenberg et al. [21] studied the problem of reducing waiting times at charging stations with adaptive EV route planning. Zhou et al. [50] focused on design and optimization of solar-powered shared autonomous EV systems for smart cities. Zhao et al. [47] performed joint order dispatch and repositioning to maximize the urban EV sharing platform's long-term cumulative profit. Tian et al. [25] designed a charging recommendation model for individual ET only after a request, but they did not consider potential charging requests and possible leave of ETs after a full charge, which will cause a suboptimal recommendation and lead to a longer queuing time. The individual-based recommendation is similar to the greedy algorithms, which may provide a single-step optimal charging station recommendation for each request. However, it cannot guarantee the global optimum for the entire ET fleet. Since the taxi fleet is controlled by the same dispatching center, leveraging the abundant fleet information may make a better decision and obtain an optimal recommendation.

2.3 Gas Vehicle Refueling

A charging process of ETs has a similar function with the refueling process of conventional gas taxis [46, 48], i.e., providing power for vehicles, but there are two key differences. First, a charging duration of ETs typically lasts for half an hour to two hours, which is much longer than a gasoline refueling duration of conventional taxis, which normally takes about 4–6 minutes [7, 46]. This long charging service time makes our modeling for ETs much more challenging than that of gasoline taxis. Second, compared with the number of gas stations across the city, the number of charging stations is much fewer. The limited charging infrastructure makes it difficult for ETs to find available charging points, which potentially causes long queuing time (e.g., half an hour). These two reasons make the charging issues different from the gas refueling problem.

2.4 Resource Allocation

There are many recent papers on resource allocation in different scenarios, e.g., mobile edge network, communication network, smart industry, IoT network, and so on. Chen et al. [6] jointly optimized the unloading decision of all users and calculated the resource allocation to minimize the total energy consumption and the maximum delay of users. Tan et al. [24] aimed to optimize the unloading decision of the tasks among all users and the allocation of computing and communication resources to minimize overall energy consumption and costs of computing and maximum delay. Yang et al. [43] considered the sum power minimization problem via jointly optimizing user association, power control, computation capacity allocation, and location planning in a mobile edge computing network. Seid et al. [22] proposed a model-free deep reinforcement learning-based collaborative computation offloading and resource allocation scheme for emergency situations. Wu et al. [41] aimed to maximize the secrecy rate of the wireless-powered relay network via a joint

optimization of power allocation and time assignment. Wang et al. [40] proposed an integrated scheduling algorithm with both future-aware and context-aware mechanisms for taxi allocation. Afrin et al. [1] comprehensively surveyed the state of the art on resource allocation and service provisioning in multi-agent cloud robotics. Peng et al. [20] determined the resource allocation strategy by the interaction among Digital Twins according to the credit-based incentives. However, few existing works focus on charging resource allocation in large-scale EV networks.

2.5 Summary

Technically, the key advantage of our method is that we fully leverage the fleet information to infer the status of *all ETs* (e.g., potential future demand) and *all charging stations* (e.g., charging queuing and service time) from a fleet perspective based on multiple sensor datasets, in contrast to existing works on recommendation from an individual level. Our objective is to minimize the overall charging overhead without building new charging infrastructure.

3 DATA COLLECTION AND ANALYSIS

In this section, we first introduce the multi-source data used in this paper, and we then conduct data analysis to uncover some insights of ET charging.

3.1 Taxi Infrastructure and Data Collection

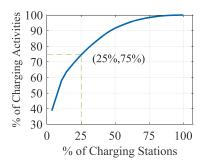
In addition to the basic taximeters, all taxis in Shenzhen are equipped with different sensing devices (e.g., GPS and camera) and communication devices [37]. Dispatching centers with cloud storage are built to monitor the operating status of all taxis and all GPS data are uploaded periodically to dispatching centers through cell towers. Charging stations with fast charging points are deployed to refuel the ET fleets for their daily operation.

In the ET infrastructure, various data have been collected for management purposes: (i) with GPS devices, vehicle attributes, e.g., vehicle IDs, and dynamic attributes, e.g., current longitudes and latitudes, time stamps, speeds, directions, and occupied flags are recorded; (ii) with taximeters, ETs record the pickup and drop-off time stamps, operating distances, cruising distances, and fares; (iii) with communication devices, both static and dynamic attributes are uploaded periodically to dispatching centers via cell towers, and then the massive GPS dataset is stored in cloud servers of dispatching centers for management; (iv) with charging devices in charging stations, ETs can charge. Each station has a station ID, a name, longitude, and latitude of the station, and the number of fast charging points in it. There are 117 fast charging stations scattered in Shenzhen in 2018.

3.2 Data Preprocessing

In this project, we are working with Shenzhen transportation committee, which operates and owns all these ET and regular taxis in Shenzhen (but charging stations are operated individually). We establish a secure and reliable transmission mechanism with a wired connection, which feeds our server the filtered ET data wirelessly collected by the Shenzhen transportation committee by using a cellular network. The filtering process replaces sensitive data, e.g., plate ID, with a serial number for privacy protection. We utilize a 34 TB **Hadoop Distributed File System (HDFS)** on a cluster consisting of 11 nodes, each of which is equipped with 32 cores and 32 GB RAM. For daily management and processing, we utilize the MapReduce-based Pig and Hive. Then we match each GPS record on the Shenzhen road network, and we filter some records that are very far from all road segments caused by GPS error (e.g., 20 meters from the nearest road segment). Due to the long-term GPS data and transaction data, we have been dealing with several kinds of errant data, e.g., duplicated data, missing data, and data with logical errors, and thus we have been conducting a detailed data curation process.

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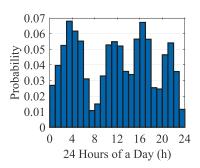


Fig. 2. Temporal distribution.

3.3 Charging Activity Definition

A complete ET **charging activity** includes three stages: (i) seeking and traveling to a station, which we call the traveling stage; (ii) queuing in a station for an available charging point to charge, so it is called the queuing stage; and (iii) being served and charged at a charging point, and this is denoted as the service stage. Likewise, the three time periods corresponding to the three stages are defined as traveling time $T_{traveling}$, queuing time $T_{queuing}$, and service time $T_{service}$. The total charging time is defined as the sum of the three items.

We designed a two-step spatiotemporal constraint-based charging activity extraction algorithm to infer the three times of ETs from their trajectories (i.e., GPS records), combined with the transaction data. For the first step, we extract the possible charging events from ETs' GPS data based on the fact that an ET will stay for a long time at the same point (i.e., same longitude and latitude) to have a charge. For the second step, we check if the possible charging event is in a charging station, which means the location of the possible charging events should be within a certain range of a charging station location in the charging station data.

3.4 Charging Pattern Analysis

In this subsection, we analyze one-month real-world data to capture some insights into the charging patterns of ETs. From Figure 1, we found that about 70% of charging activities happen in 25% of charging stations. It is understandable that most ETs always operate in the business area since there is higher passenger demand. More importantly, drivers are more likely to cruise in the area with more charging stations to avoid low-range anxiety.

Figure 2 shows the temporal distribution of charging activities. It is clear that most charging activities happen at some time slots, e.g., early morning (2:00–6:00), midday (10:00–13:00), and early evening (20:00:22:00). The intensive charging and frequent charging activities potentially cause severe charging resource competition phenomena, which result in a longer queuing time in charging stations.

Figure 3 shows **cumulative distribution function (CDF)** of charging service time. We found that about 85% of charging activities consume half an hour to one and half hour, and over 97% of charging activities last for half an hour to two hours. Based on the historical charging data, we can understand the charging pattern for each particular ET and predict the charging service time.

Insights. Based on the above charging pattern analysis, we provide the following observations: (i) there is an uneven spatial and temporal charging pattern. For the unbalanced spatial pattern, 58% of charging activities happen in 10% of charging stations. For the uneven temporal pattern, there are four distinct charging peaks, resulting in overcrowded charging stations at these times while underutilized charging stations during other periods; (ii) 97% of charging service time would

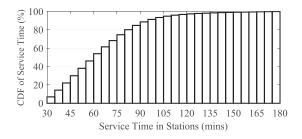


Fig. 3. CDF of charging service time.

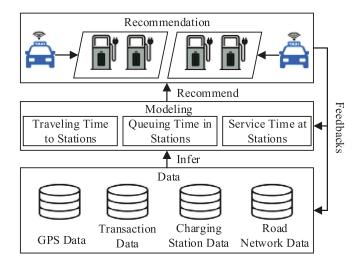


Fig. 4. Overview of the ForETaxi.

be half an hour to two hours for ETs, which results in potential operation time reduction than gas taxis, so it is important for us to obtain an optimal charging station deployment strategy or design an intelligent charging recommendation system to address these charging issues. However, it is difficult to site abundant charging stations for ETs due to some real constraints, e.g., unavailable land resources.

Hence, it is necessary for us to design a charging recommendation system, which informs drivers where/which charging stations to charge for addressing the uneven charging demand problem and improving the charging efficiency of the current charging network based on only existing charging stations.

4 SYSTEM MODELING AND DESIGN

4.1 Overview of the ForETaxi

In this paper, we design a fleet-oriented charging recommendation system called ForETaxi to improve the charging efficiency of ETs, which includes a three-layer data-driven architecture for ET fleet modeling and charging recommendation, as shown in Figure 4. The bottom layer is the multi-source data layer, which collects and stores data from the ET infrastructure and lays the data foundation for charging modeling and recommendation. The second layer is the charging activity modeling layer, which models the charging activities of ET fleets, including seeking and traveling activities to charging stations, queuing activity at stations for available charging points,

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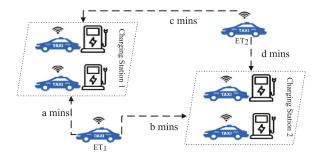


Fig. 5. An example of charging recommendation.

and service activity at stations. In the top layer, i.e., the charging recommendation layer, we use the information obtained from the charging modeling layer to recommend ETs to corresponding charging stations, and the overall objective is to minimize the total charging time of all ETs and maximize the operating time of the fleet. After each recommendation decision, the status of charging stations will be updated in the data layer, which will be used by modeling and recommendation layers again in an iterative way.

In this next part, we describe the system modeling and recommendation design in detail, including charging activity modeling and charging recommendation. We present a vehicle-specific energy and time consumption model at road segment levels, and then calculate the three time overheads, i.e., $T_{traveling}$, $T_{queuing}$, $T_{service}$ based on inferring the status of ETs. The models of $T_{traveling}$, $T_{queuing}$, $T_{service}$, as well as the parameters of the three models, are learned from our large-scale data and field studies, so they should be more practical compared to existing models. Suppose there is an ET fleet in a city, including n_{et} ETs, and all these taxis are managed by a dispatching center so taxis can coordinate with each other. Without loss of generality, we take one day as a basis and then iterate the model to obtain a long-term and effective charging recommendation for the fleet.

4.2 $T_{service}$ Inference

In this subsection, we first clarify why it is significant and meaningful to consider the $T_{service}$ for charging recommendation by real charging scenarios. Then we analyze the historical data to investigate the spatial and temporal charging patterns, i.e., (i) charging events distribution in different charging stations, i.e., spatial distribution; (ii) charging events distribution in different hours, i.e., temporal distribution; and (iii) the duration of charging service time for each charging event. Finally, we obtain the energy and time consumption models to estimate the service time for each charging event, which is then used for the $T_{queuing}$ inference in Section 4.4.

4.2.1 Importance of Considering $T_{service}$. We show the significance of $T_{service}$ by describing some ET charging scenarios. We also show how we leverage existing charging infrastructure to reduce the overall charging time for ET fleets and why fleet-oriented recommendation can leverage service time to achieve better performance than individual-based recommendations or recommendations without considering the service time, which is also the difference between individual-based recommendations and our fleet-oriented recommendation.

As shown in Figure 5, there are two charging stations, i.e., charging station 1 (CS_1) and charging station 2 (CS_2), and there are two charging points in each station. The time labeled near each line stands for the traveling time to a station.

Scenario 1: a = 10, b = 15, c = 12, and d = 15, and there is an available charging point in each station. An individual-oriented recommendation system adopts the first come first served policy. If

 ET_2 sends a request first, it will be recommended to CS_1 by the individual-oriented system. At this time, if ET_1 requests a recommendation, the system will recommend it to CS_2 . The total traveling time is 27 minutes without queuing time. But if we consider the status of all ETs in the fleet and predict the request from ET_1 , we can recommend ET_1 to CS_1 and ET_2 to CS_2 to obtain a global optimization with 25 minutes' traveling overhead with zero queuing time. In this case, the fleet information (e.g., the possible charging requests) has not been considered in individual-oriented recommendation, and we can save about 8% (2 minutes) as for the total $T_{traveling} + T_{queuing}$ if we consider from a fleet perspective.

Scenario 2: a = 10, b = 15, c = 20, and d = 15, and all charging points are occupied. If only considering to recommend the drivers to the stations with shortest traveling time, the ET_1 will be recommended to CS_1 and the ET_2 will be recommended to CS_2 . However, in fact, the two ETs served at CS_1 will leave in 20 minutes but the two ETs at CS_2 will leave after 30 minutes. In this case, we should recommend ET_1 and ET_2 to CS_1 to reduce its queuing time and overall charging time. Hence, if the charging status of each taxi has been estimated in advance, a better recommendation may be obtained, this is why the service time is important for the charging recommendation, even though the service time itself would not have significant differences by leveraging different recommendations. In this case, if we utilize the fleet information, i.e., the status of ETs being served at stations, we can save 40% (10+20+0+0 compared to 10+15+10+15) of the $T_{traveling} + T_{queuing}$ during this recommendation process. Hence, such fleet information can be useful for reducing the overall charging time, but it has not been considered by individual-oriented methods.

4.2.2 Calculation of $T_{service}$. The duration an ET served at a charging point is decided by the current **State of Charge** (i.e., **SOC**) of the ET and the charging rate of the charging point, i.e., fast charging points or slow charging points. If the battery level is too low, drivers will spend more time on charging, and vice versa. Likewise, if the charging point has low charging rates, it will cost more time for drivers to have their taxis fully charged. The current battery power of an ET is related to the distance and time it has traveled since the last charge. Higher cruising mileage will consume more energy. Similarly, a longer operating time will also lead to low battery capacity. For example, if the traffic is heavy, the drivers will spend more time going to the same destination. Hence, in this case, even though the traveling distance of the ET is not too long, the battery consumption is high. Considering these factors, a linear model can be built to estimate the battery status of each ET [13, 17, 42]. According to two field studies [3] in Shenzhen, the battery consumption rate of the BYD e6 ETs is related to cruising speeds. The battery consumption model and the depletion rate can be expressed as follows:

$$C_{t_2} = C_{t_1} - \sum_{l=1}^{n} d_l \cdot u_l$$

$$= C_{t_1} - \sum_{l=1}^{n} v_l \cdot t_l \cdot u_l$$
(1)

$$u_{l} = \begin{cases} 2.03 & v \ge 80km/h \\ 2.6 & 20 \le v < 80km/h \\ 1.53 & v < 20km/h \end{cases}$$
 (2)

Where C_{t_2} is the current battery capacity; C_{t_1} is the original battery power at time t_1 ; d_1 is the distance traveled on a road; u_l is the battery consumption rate on road segment l, which denotes the distance an ET can cover with 1% battery capacity and it is decided by the speed of the road segment. Here we assume that the speed under 20km/h is caused by the traffic jam, so the battery consumption is relatively large. It is expected that the ETs will have charging requests when

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the SOC is lower than a threshold [17]. According to [2], the *range anxiety* of ET drivers will be extremely strong when the battery power is lower than 13% and they are eager to charge, so we assume ETs have potential charging demand when the battery power is around 13%, which is used for charging requests prediction.

If all fast charging points have the same charging rate, similar to the energy consumption model [23], a linear charging model can be built to estimate the service time at charging stations. Since it needs two hours to fully charge an ET and the maximum battery capacity is 57 kWh, for simplicity, the average charging rate is set to 0.8333% per min. The charging model can be described as the following:

$$T_{service} = \frac{C_{full} - C_{sc}}{r_{ch \arg e}} \tag{3}$$

Where C_{full} is different from different ETs since they have various operational time and maximum battery capacities. It can be estimated by their maximum traveling distance, which can be inferred from the transaction data. C_{sc} is the current SOC and it is decided by the distance an ET has traveled since the last charging activity and the traffic conditions.

4.3 $T_{traveling}$ Inference

4.3.1 Start and End Points of $T_{traveling}$. According to [16, 25], drivers usually submit a charging request after dropping off a passenger and it has also operated a certain distance since the last charge, leading to a low battery level. Hence, the start point of the traveling stage is the time when the last passenger gets off the ET before a charging event. We merge the transaction data from the onboard vehicle equipment and charging activities from GPS data to obtain the start points since the last drop-offs, and the charging events are adjacent and disjoint. Due to the limited battery capacity, ETs can only operate a certain amount of miles after a full charge. The maximum traveling distances are decided by their full battery capacity, which can be calculated by combining the transaction data and charging events, so the operation distance of an ET after charging must be shorter than the maximum traveling distance. The endpoint of the traveling stage is the time when the ET arrives at a charging station and starts queuing for charging. The time interval between the two points is the traveling time to a station, which is decided by the distance and the road condition to a station at this time.

4.3.2 Calculation of $T_{traveling}$. In this subsection, we present a vehicle-specific time consumption model at road segment levels in real time for more precise status modeling. Since the destinations of passengers could be any place in the city and the drop-off locations can be anywhere, the routes to a charging station may not appear before, and it is necessary to estimate the speed of each road and then infer the time from any place to a station. The existing research [49] shows that the workdays typically have similar traffic conditions and patterns, while the weekends have different patterns compared to workdays. We use historical trajectory data to predict the average speed on each road segment on workdays and weekends. We empirically select 5 minutes as a time slot to update the estimation value because of the dynamic characteristic of the traffic flows. We also compare performances with different slot lengths in Section 5.4.1.

A road network can be seen as a graph consisting of road segments and intersections. The road segments are the edges of the graph. The intersections and endpoints of the road segments are the vertices of the graph. The traveling speed of each road segment can be seen as the weight of the edge. Notably, to a bidirectional road segment, the traffic conditions from different directions are different. Suppose there are m intersections and n road segments in a city, and the road network of the city can be represented by a **directed graph (DG)** G = (I,R), where $I = I_1 \cup I_2 \cup \cdots \cup I_m$, $R = R_1 \cup R_2 \cup \cdots \cup R_n$. We utilize all historical GPS data of all vehicles to estimate the travel speed

at a fine-grained time slot since our GPS data includes the real-time vehicle speed. We denote the average traveling speed at time t in workdays as $v_{R_{ij}}(w_o, t)$, and weekends as $v_{R_{ij}}(w_e, t)$, where R_{ij} denotes the road segment from intersection I_i to intersection I_j . Thus, two average speed matrixes at time t can be obtained, representing the traveling speed of each road segment for workdays and weekends.

After obtaining the average speed of each road segment, we estimate the traveling time between any two locations L_1, L_2 using the following formula

$$T_{(L_1,L_2)}(w_o,t) = \sum_{s=1}^k \frac{D'_{R_s}(w_o,t)}{v_{R_s}(w_o,t)},$$
(4)

$$T_{(L_1,L_2)}(w_e,t) = \sum_{s=1}^k \frac{D'_{R_s}(w_e,t)}{v_{R_s}(w_e,t)},$$
(5)

where k is the number of road segments between L_1 and L_2 ; D'_{R_s} is the length of road segment R_s ; v_{R_s} is the average speed of corresponding road segment R_s . Thus, two speed matrices can be built to estimate the traveling time on road segments on different days.

4.4 $T_{queuing}$ Inference

If an electric taxi ET_i starts seeking a charging station at time t_1 , the $T_{queuing}$ is decided by the number of ETs served in the station and the ETs arriving at the station before ET_i arrives. It should be noted that the number of ETs served and waited in a station should be the number when ET_i arrives at the station t_2 , because there may be some ETs that got fully charged and left when ET_i arrives at the station t_2 , and there may also be some ETs arriving at the station earlier than ET_i . That is why we need to estimate the charging service time of each ET. In this case, it may be not optimal to recommend the ET to the charging station with the nearest distance or the shortest time. In certain circumstances, when an ET heads to a station, there may be other ETs submitting charging requests at the same time or near future, so they can coordinate with each other to avoid long queuing times. In other cases, even though there are no available charging points when they send requests, there may have some points available when they arrive at the station since some ETs will be fully charged and ready to go at that moment, so it is also important to estimate the charging status of ETs that are charging. If there are available points when an ET arrives at a station, the queuing time is 0.

Based on the fleet information, we design the fleet-oriented optimal queuing algorithm, which is shown as Algorithm 1, where T^i_{leave} stands for the time when i^{th} ET is fully charged and leaves, leading to an unoccupied point.

4.5 Charging Request Prediction

A key component that needs to be predicted is the number of charging requests in the near future. In this work, we fully utilize our large-scale long-term data to extract patterns for prediction. Particularly, we consider different real-world factors to predict the charging requests accurately (historical request, spatial features, temporal features, and contextual features like weather conditions, etc.). Firstly, we divide the city into $100m^*100m$ of grids for fine-grained prediction. We also divide one day into 288 time slots, and each slot is 5 minutes. we collect meteorology data from the website [26] and extract features for the net flow prediction. We identify three contextual features: weather, temperature, and wind speed. Among these features, the weather feature is divided into three categories: sunny (or cloudy), rainy, and snowy. The temperature feature has also three types of values: cold (lower than 15° C), mild ($15-30^{\circ}$ C), and hot (over 30° C). The wind speed is divided into two categories according to the Beaufort number: light (≤ 3) and heavy (> 3). Then we utilize

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ALGORITHM 1: Fleet-Oriented Queuing Time

```
Input:
     s: a charging station;
     ET_r: an ET to be recommended;
     T_{arrive}: time arrive a station;
     N_p: the number of charging points;
     N_s: the number of ETs served at the station;
     N_e: the number of ETs arrive early than ET_r.
Output:
     T_{queuing};
  1: Begin
  2:
           If N_p-N_s-N_e > 0
  3:
              T_{queuing} = 0
  4:
            Else
  5:
               For each ET_i in (E_s \cup E_e)
  6:
              \begin{split} &\text{Infer leaving time } T_{leave}^{i} \\ &T_{queuing} = min\{T_{leave}^{Np-Ns-Ne} - T_{arrive}\} \end{split}
  7:
  8:
  9:
10: End
11: return Tqueuing;
```

a widely-adopted spatial-temporal prediction method [44] to predict the charging requests in the near future, which has the capability to capture the spatial relation (e.g., using CNN) and temporal relation (e.g., using LSTM) at the same time.

To now, we have designed a vehicle-specific energy and time consumption model at road segment levels to infer the traveling time, queuing time, and charging service time of a particular ET based on the status of all relevant ETs in the fleet. In the next part, we will leverage these inferences to make charging recommendations for the ET fleet.

4.6 Charging Recommendation

Passenger demand has also been considered a constraint to recommend ETs to charging stations to reduce potential income loss of drivers. As shown in Figure 2, we will recommend the number of ETs to charging stations in inverse proportion to the number of passengers, which means we will recommend more ETs to charge when the passenger demand is low and charging demand is high and recommend fewer ETs to charge when the passenger demand is high and charging demand is low. Thus, the recommendation system would have little impact on the mobility of the city and

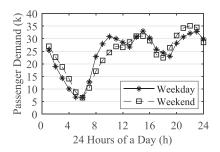


Fig. 6. Passenger demand.

potentially do not affect the income of ET drivers. We leverage all taxis' transaction data (including gas taxis) to infer the passenger demand, as shown in Figure 6.

From Figure 6, we found that the passenger demand has an increase or decrease trend for every 6 hours, e.g., the passenger demand has a decreasing trend from 0:00 to 6:00 am, so we potentially recommend more ETs to charge when the time is close to 6:00 am. Under normal circumstances, we do not interfere with drivers' requests. When the number of charging requests reaches a threshold,

we do not consider potential charging requests and only deal with these submitting ones. The recommendation number threshold is decided by the total number of available charging points and the historical charging request distribution every 6 hours. For example, if the available charging points are 100, we would not consider extra charging requests more than 100 ETs to charge. These numbers are obtained from our real-world data.

Based on the charging time estimation and the passenger demand, the system will make realtime decisions for ETs. The process of the fleet-oriented charging recommendation algorithm is given in Algorithm 2, which we sum up one-day recommendation together. Charging activity modeling in Sections 4.2, 4.3, and 4.4 is embedded in Algorithm 2. The insight of this algorithm is that the service time is embedded in Algorithm 2 and the possible charging requests are also considered for a recommendation, which is shown in lines 6 and 7 of Algorithm 2. Besides, the passenger demand is also considered as a constraint when recommending, which is in line 9 of Algorithm 2. These three components distinguish our method from existing works.

ALGORITHM 2: Charging Recommendation Process

```
Input:
     An ET Fleet, Charging Stations, Number of Time Slots;
Output:
     Corresponding Stations;
 1: Begin
 2:
        \forall s \in S
           For m = 1 to n_{ts} do
 3:
              For k = 1 to n_{et} do
 4:
                  T_t(s, k, m) inference from Section 4.3;
 5:
                  Algorithm 1 in Section 4.4;
 6:
                  T_s(s, k, m) inference from Section 4.2;
 7:
 8:
              End
              If \sum_{i=1}^{N_{ts}} N_{et_i} \leq N_{thre}

SumInSlot \leftarrow \sum_{k=1}^{n_{et}} (T_t(s, k, m), T_q(s, k, m), T_s(s, k, m));
 9:
10:
11:
           SumInDay \leftarrow \sum_{k=1}^{n_{ts}} SumInSlot;
12:
        Min(SumInDay);
13:
14: End
15: return Corresponding Stations;
```

We aim to recommend a fleet with n_{e_t} ETs to charge, and we first split one day into n_{t_s} time slots. We then estimate the speed on each road segment and the number of ETs that need to charge in the time slot. After a charging request submitted by a driver, we leverage Equations (4) or (5) to estimate the traveling time of ET k to station s at time slot $m T_t(s, k, m)$ based on historical data. Likewise, we leverage $T_q(s, k, m)$ to stand for the queuing time of ET k in station s at time slot m and calculate it by using Algorithm 1, and we calculate the service time of ET k at station s at time slot $m T_s(s, k, m)$ as shown in Section 4.2.2. Then we add all items together to obtain the total charging overhead of one ET. $T_t(s, k, m)$ is calculated by using Equations (4) and (5), which is the total traveling time on each road segment to station s. $T_s(s, k, m)$ is decided by the current battery status if all charging points have the same charging rate. Current battery status can be estimated based on Equations (1) and (2). After estimating the current battery status, we use Equation (3) to estimate the service time at a station. It should be noted that the difference of service time in different charging stations is decided by the road conditions, e.g., road length and speed on the

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road, which can induce different energy consumption, so the $T_s(s,k,m)$ is related to the traveling route and traveling time, namely, which station is to be recommended.

After we estimate the service time of each ET, we estimate their full charge time and then infer the number of ETs served in the station when an ET arrives at the station. Hence, the $T_a(s, k, m)$ is decided by the ETs served at stations. In each time slot, we recommend all ETs with possible requests to corresponding stations by minimizing the overall charging time. Once we perform a recommendation, we add all recommendations in one day to obtain the optimal recommendation results in this day, which can be formulated as Equations (6)–(8).

$$S^* = \arg\min_{s \in S} \sum_{m=1}^{n_{ts}} \sum_{k=1}^{n_{et}} \left[T_t(s, k, m) + T_q(s, k, m) + T_s(s, k, m) \right]$$
 (6)

$$s.t.: \sum_{i=1}^{N_{ts}} N_{et_i} \le N_{thre}$$

$$N_{thre} = f(N_{td})$$
(8)

$$N_{thre} = f(N_{td}) \tag{8}$$

where S is the set of charging stations; s is a station in the set; S^* is the recommendation result; N_{thre} is the threshold number to recommend, which is denoted by a function of passenger demand N_{td} ; N_{ts} is the number of time slots in 6 hours; and N_{et} is the number of requests in each time slot.

The most challenging components of solving (6) include estimating the $T_{traveling}$ and $T_{queuing}$, and then minimizing different possible combinations of charging times of ETs as $T_{service}$ can be estimated when we know the status of the ET (e.g., location and battery level) when it sends the request. To directly solve (6) would be complexity intractable due to a large number of possible paths to charging stations, a large number of ETs in the fleet, and concurrent requests. Hence, we first adopt pruning to reduce the feasible search space. The basic idea is that we limit the number of charging stations that each ET can go to an appropriate range instead of the entire charging network. The intuition is that the traveling time is highly correlated with the traveling distance, so we can select several near charging stations to guarantee a short traveling time for the ET. The specific number is decided by different real-world factors (e.g., the size of the fleet, the charging network, and the city), and it is set as five in our work after carefully comparing different values. There are three key factors that impact the $T_{queuinq}$, i.e., the number of charging points in each station N_p , the number of ETs served at the station N_s , and the number of ETs that arrive earlier than the ET to be recommended N_e . N_p is static data and has been stored in our database. N_s is dynamic data and will be updated and stored in our database periodically, so which will also reduce the computational complexity. N_e is decided by other ETs that have charging requests now or in a near future, so it will be decided when we try different combinations. The most challenging part for recommendation is to coordinate the ETs for higher charging efficiency since it is a largescale nonconvex nonlinear optimization problem. To address this problem, in this work, we adopt the simulated annealing algorithm [14, 19] to find the approximate global optimization in the large search space. The reason is that the simulated annealing algorithm is effective when the search space is discrete. Even though simulated annealing cannot always be guaranteed to find the globally optimal solution, but it does usually produce a good solution. In our scenario, finding an approximate global optimum is more important than finding a precise local optimum given a limited time for the real-time requirement.

5 **EVALUATION**

In this section, we start by introducing the real-world datasets for evaluation. Then several metrics are defined to compare our system with other state-of-art recommendation methods. Finally, we

investigate the impacts of time slots, recommendation-following rate, and fleet sizes on the system performance of ForETaxi.

5.1 Datasets

A real-world dataset introduced in Section 3 is leveraged to validate our ForETaxi. We utilize one week of GPS records from more than 13,000 ETs and metadata of 117 charging stations in 2018. More than 11.9 million transaction records are generated by ETs during this duration. The numbers of road segments and intersections are 135,138 and 87,514, respectively, in Shenzhen city.

5.2 Metrics and Baselines

We define Percentage of Reduced Queuing Time, Percentage of Reduced Service Time, and Percentage of Reduced Charging Time as three key metrics to show the system efficiency. Assuming the actual average queuing time is τ , φ is the average queuing time of a specific recommendation, then the Percentage of Reduced Queuing Time equals to $\frac{\varphi-\tau}{\tau}$.

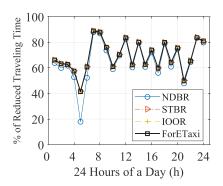
Three other individual-oriented charging recommendation strategies, i.e., the nearest distance-based charging recommendation (NDBR) [16] and the shortest traveling time-based charging recommendation (STBR) [8] and the individual-oriented optimal recommendation (IOOR) system [25], are compared with our fleet-oriented optimal recommendation system ForE-Taxi. For the individual recommendation, they are local greedy algorithms, which means they serve the driver who sends a charging request without considering other potential requests.

We first extract the speed of each vehicle in a short time slot and then conduct map matching to estimate the average traveling speed on each road segment at different times. This speed will be used for the traveling time estimation to feed to the algorithm. We also extract the charging requests based on our data. The intuition is that drivers usually submit a charging request after dropping off a passenger and it has also operated a certain distance since the last charge, leading to a low battery level. Hence, the charging request will be sent when the last passenger gets off the ET and the battery capacity also decreases to a low level. That is to say, we merge the transaction data and charging activities extracted from GPS data by a two-step spatiotemporal constraint-based extraction algorithm [36] to obtain the charging requests. We then further calculate the operation distance of the ET since the last charging by merging the transaction data and the charging events. Then the service time can be estimated with Equations (1)–(3). There are three key factors that impact the charging queuing time, i.e., the number of charging points in each station N_p , the number of ETs served at the station N_s , and the number of ETs that arrive earlier than the ET to be recommended N_e . N_p is static data and has been stored in our database. N_s is dynamic data and will be updated and stored in our database after each round of recommendations. With the predicted number of charging requests in the near future, we will feed our static and dynamic data into Algorithm 1 to infer the queuing time of the ET when it is recommended to different charging stations. Then we store the queuing time in our database. With all possible combinations of estimated traveling time, queuing time, and service time, we then feed them into Algorithm 2 to find the approximate global optimization in the large search space.

5.3 Comparison Results

5.3.1 Comparison of Traveling Time to Stations. In this subsection, we compare the performance of different recommendation systems using the metric Percentage of Reduced Traveling Time. As shown in Figures 7 and 8, the NDBR has the smallest Percentage of Reduced Traveling Time. The other three recommendation systems achieve better performance, with more reduction of traveling time. The reason may be that even though the station is the nearest one to an ET, the traveling time to the station may be long because of the traffic conditions, i.e., traffic congestion. STBR obtains

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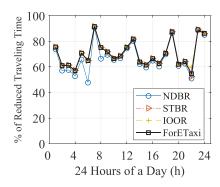


Fig. 7. Traveling time in workdays.

Fig. 8. Traveling time in weekends.

the optimal traveling time but the IOOR and ForETaxi also achieve good performance with just several seconds longer. Both two figures show that the least Percentage of Reduced Traveling Time is around 5:00 in the morning and the traveling time is long in the early morning. The reason may be that drivers operate the ETs in the urban business areas and they will change shifts at suburban areas where ET drivers live and charging stations are built. The distance from urban business areas to suburban is very far, thus, although the traffic conditions are fair at this duration, the traveling time is still long. Another change shift time is around 16:00, so the traveling time to the stations is also longer in this duration.

Comparing Figure 7 with Figure 8, we found that the Percentage of Reduced Traveling Time is different between workdays and weekends since there are different distances to charging stations, traffic conditions, and various traveling patterns of citizens. ETs will spend more time on the way to stations at rush hours on workdays than on weekends because there may be a heavy traffic jam on workdays, i.e., 7:00 and 18:00. But the traveling time to stations around 20:00 on weekends is longer than on workdays since more vehicles travel at this moment, leading to traffic jams.

5.3.2 Comparison of Charging Queuing Time. Figures 9 and 10 shows the Percentage of Reduced Queuing Time in different hours for workdays and weekends. The negative numbers denote that the average queuing time using this method is longer than the ground truth. This is because too many ETs operate in urban business areas. If using NDBR and STBR recommendations, there are too many ETs that will be recommended to the same charging stations, leading to an increase in the queuing time. During charging peak hours in one day, e.g., 3:00–6:00, 11:00–13:00, 16:00–18:00, 21:00–23:00, it will waste more time for drivers to wait for an available charging point. The charging peak durations are usually in break and mealtime and lower passenger demand is in these durations, so it would not cause much income loss to drivers. In our recommendation system, we also follow this intuition by recommending more ETs to charge when passengers' demand is low and few ETs to charge if passengers' demand is high.

It can be seen from Figures 9 and 10, our method achieves the largest decrease in terms of the queuing time. There are some differences between workdays and weekends. The passenger demand in the early morning on weekends is high, so few ETs are recommended for charging at this time slot, leading to a short queuing time. More ETs are recommended to charge between 7:00–9:00 on weekends than on workdays since people will have more rest and do not need to work on these days, so there is lower passenger demand. Likewise, few ETs will be recommended to charge in the afternoon on weekends since more people will go out causing higher passenger demand, so the queuing time is short on workdays compared to weekends. In general, we found Our ForETaxi reduces 83% and 82% of queuing time compared to the ground truth and NDBR, respectively.

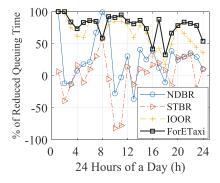


Fig. 9. Queuing time in workdays.

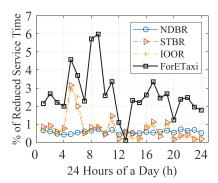


Fig. 11. Service time in workdays.

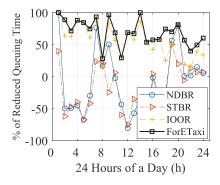


Fig. 10. Queuing time in weekends.

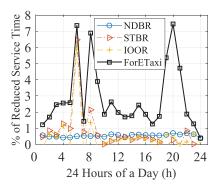


Fig. 12. Service time in weekends.

5.3.3 Comparison of Charging Service Time. In this subsection, we compare the performances of different recommendations using the metric Percentage of Reduced Queuing Time. From Figures 11 and 12, we find that all recommendation systems have a smaller percentage decrease of service time for the fleet since the SOC is similar when an ET submits a charging request. The difference in the service time between various systems is decided by the road conditions and traveling time to stations. As we describe in Section 4.2, different road speeds will lead to different battery consumption rates. There is a big difference between workdays and weekends, but our system can keep obtaining slightly better performance in terms of this metric.

5.3.4 Comparison of Overall Charging Time. In this subsection, we compare the overall charging time of different recommendation methods, which is also the objective of our charging recommendation. From Figure 13, we found that all of the four methods can reduce the overall charging time to some degree, and our ForETaxi achieves the best performance.

In this subsection, we compare the performance of different recommendations using the metric average service time at stations. From Figures 11 and 12, we can see that all recommendation systems have similar service time for ETs since the electric capacity is constant when an ET sends a charging request, so the service time difference of various systems is decided by the road condition and traveling time to stations. As we describe in Section 4.2, different road speeds will lead to different battery consumption rates. There is a big difference between workdays and weekends, but our IOOR can keep obtaining a little better performance as this metric.

From Figure 14, we found our system achieves better performance than the other three methods, especially NDBR and STBR. The queuing time of 90% charging activities would be less than 10 minutes by using our ForETaxi recommendation, while only 70% by using STBR and NDBR.

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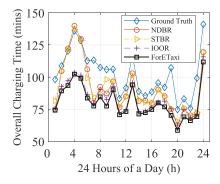


Fig. 13. Charging time in each hour.

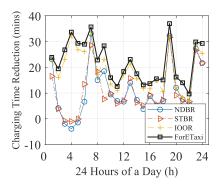


Fig. 15. Time reduction distribution.

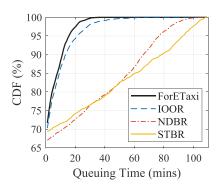


Fig. 14. CDF of queuing time.

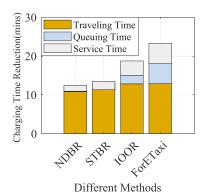
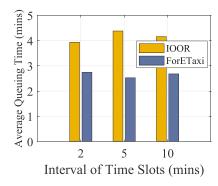


Fig. 16. Overall time reduction.

To have a better understanding of the overall charging time reduction, we also show the charging time reduction of different recommendation methods in Figures 15 and 16, and we found our recommendation can achieve the largest charging time reduction. For example, ForETaxi reduces 29% of total charging time compared to the ground truth and reduces 16% of total charging time compared to NDBR. In total, the average traveling time + average queuing time of our ForETaxi is about 445s for one charging activity, while NDBR is 1207s and IOOR is 520s. Moreover, ForE-Taxi saves 94s service time for drivers compared with IOOR. In fact, the IOOR has a good recommendation for the ETs if other vehicles' status is not available. Our more advanced design for ForETaxi is to further advance the ET charging recommendation with our fleet-oriented solution. Compared with NDBR, STBR, especially for the ground truth, the IOOR and ForETaxi saved over 30 minutes for each charging. Our fleet-oriented recommendation can reduce 4.407 and 23.467 minutes compared to IOOR and the ground truth. In particular, for each ET, it charges about 3.5 times a day, so our ForETaxi can reduce about 200,518 minutes of charging time compared with the optimal individual recommendation IOOR for the ET fleet per day based on our data. This 200,518 minutes reduction can make the ET fleet serve additional 11,460 passengers in one day, which can potentially improve passengers' satisfaction and enhance the mobility of the city. With more and more taxis replaced by electric vehicles, we believe our recommendation has the potential to achieve better performance compared with IOOR based on our evaluation, and our design should have higher benefits compared to the supplementary cost (e.g., communication and complexity).





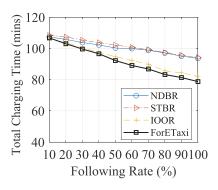


Fig. 18. Impact of following rates.

5.4 Impact of Factors

5.4.1 Impact of Slot Length. In the previous investigation of the paper, we empirically divide 24 hours into a total of 288 5-min slots. For a particular slot, we calculate the average speed of each road in one day. In order to investigate the impact of slot lengths on performance, we split one day into different slots, e.g., 2-min, 5-min, and 10-min for comparison.

Figure 17 shows the average queuing time in stations. We found that our ForETaxi achieves better performance than IOOR, e.g., the average queuing time is about 40% less than IOOR, but the queuing time is similar between different time slots since the queuing time is irrelevant to the slot length.

5.4.2 Impact of Recommendation-Following Rate. In the previous setting, we assume all drivers will follow our recommendations, but in reality, some of them will not follow the recommendation. In this subsection, we show the system robustness when some ET drivers do not follow our recommendations and show how they may affect the system as a whole. We consider the drivers who obtain a much longer charging time than they usually have or expect will have a higher probability to reject our recommendation instead of randomly selecting them. As shown in Figure 18, the system performance of the four recommendation systems will increase with the recommendation-following rate increase, but our ForETaxi achieves a higher gain of charging time reduction with high participating rates. Especially, when more drivers follow our recommendation, the average total charging time will be lower for the ET fleet.

5.4.3 Impact of Different Fleet Sizes. To further verify the generalizability of our recommendation method under different fleet sizes, we further study the recommendation performance under the various amount of data by using five-year data (from 2014–2018) from Shenzhen, during this duration the number of ETs has increased from about 500 to over 13,000 and the number of charging stations has also increased. More details about this dataset can be found in [30]. For all the five-year data, we utilize the GPS data of all taxis (including both gas taxis and ETs) to estimate the travel time accurately since more GPS data can lead to more fine-grained real-time travel speed on each road segment.

As shown in Figure 19, we found the total charging time has a decreasing trend with the increase of the

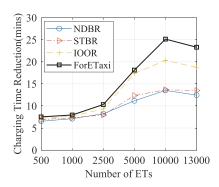


Fig. 19. Performance with different number of ETs.

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number of ETs in the fleet. When there is a small-scale ET fleet (e.g., less than 1,000 ETs), the performance of different methods is similar although our system is slightly better than other methods. While the number of ETs is over 2,500, our system achieves much better performance compared to other methods, and the charging time reduction reaches a peak when the number of ETs is around 10,000. One possible reason is that the queuing phenomenon is not severe when the ET fleet size is not too large, so the original charging time of ETs is also small. When there are more ETs, the competition between ETs for charging resources will become fierce, which leads to a much longer charging queuing time, so it is more necessary to have a fleet-oriented charging recommendation system to improve the overall charging efficiency. The reason why the maximum charging time reduction happens when the number of ETs is around 10,000 is that the number of charging stations did not increase as fast as the increase of ETs, which leads to a much longer queuing time for ETs. To summarize, our ForETaxi can achieve better performance than other methods under different number of ETs, and the performance will be more significant when the fleet size is large (e.g., the number of ETs is larger than 1,000).

5.5 Simulator Implementation

To make our method and system more accessible to other researchers, we design and share an ET simulator that includes the ForETaxi and other existing methods in it. We utilize the real-world data from Shenzhen for simulation. The simulator can show the system performance more visible and dynamic, and it also has the potential to be used by other researchers for simulating their algorithms because the parameters in the simulator are adjustable. Our simulator includes a backend server and a frontend UI interface.

5.5.1 Backend Server. The backend server is built upon the flask framework, which is a light-weight WSGI web application framework with the ability to scale up to complex applications. It allows the developer to customize the tools, libraries, and layouts they want to use. The backend flask server has three key functions: data processing, algorithm execution, and route generation.

Data Processing. In this step, the charging station information, ET information, and passenger requests will be parsed into the server. The data of charging stations include their latitudes, longitudes, and the number of available charging points. The data of ETs include their locations, operation status, and charging information, and so on. Passenger demand will be generated according to the historical distribution at that time. Based on these data, we can obtain the actual queuing time and charging time of ETs in the charging station.

Algorithm Execution. After setting the number of ETs, we can run the simulator, which will apply different algorithms to make recommendation decisions, e.g., NDBR and our fleet-oriented ForETaxi. These algorithms will assign the charging stations for the ETs to charge. Our ForETaxi will optimize the charging efficiency of the ET fleet by considering traveling time to stations, queuing time, and service time at stations. The queuing time will also be shown on the simulator.

Route Generation. After deciding which charging stations the ETs need to go to, we also generate the routes from the current locations of ETs to charging stations. we leverage the Google Maps API to display the routes. The Google Maps provides a geographically enabled Web 2.0 service [12]. When an ET has no charging need, it will serve passengers. The routes for serving passengers will also show on the simulator.

5.5.2 Front UI Interface. The UI interface is designed as web-based using the Google Map API and flask. The Google Map API provides a map for the whole Shenzhen city with millions of streets and the road network. We can also zoom in and zoom out the map to show different regions. An example of our UI interface is shown in Figure 20. The blue charger icons on the map mean ET charging stations deployed across the city. Each white circle icon means an ET in the fleet, and we

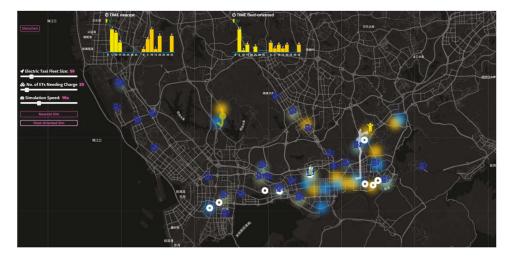


Fig. 20. The interface of the ET simulator.

utilize different colors to show various statuses of ETs. For example, the white color means the ET is cruising; the yellow color means the ET is serving passengers; and the green color means the ET is charging. There is also a dynamic green bar behind the ET when it is charging. When the ET is queuing for a charging point, there will be a red clock behind it. We also show the queuing time of different algorithms using the bar charts for comparison. We also set a simulation speed parameter for users' convenience.

6 DISCUSSION

Lessons Learned. (i) Based on our data-driven analysis, we found there is an uneven spatial and temporal charging pattern of the ET fleet, and it is possible for us to design a charging recommendation system to address this issue and improve the charging efficiency of the fleet. (ii) We found the fleet information (e.g., charging service time and potential future charging requests) is very important for the recommendation system, but it is rarely considered by existing works. (iii) Our simulator can potentially provide a platform for other researchers to understand the mobility can charging patterns of ETs, as well as verify their charging recommendation systems.

Existing Mobile Apps. Although some charging station providers have their own apps to show their charging station status, they cannot have access to other providers' charging station information due to the business competition, e.g., there are eight ET charging station providers in Shenzhen. Such incomplete information is not enough for fleet-oriented charging recommendation, resulting in suboptimal solutions. Moreover, these apps can potentially worsen the current charging situation, e.g., navigating more drivers to the same station without coordination and causing a severely crowded phenomenon. Hence, it is meaningful for us to design a fleet-oriented charging recommendation system by considering the city-scale station and vehicle information.

Impact of Private EVs and Multiple ET Fleets. In the Chinese city Shenzhen (i.e., the city that the paper focused on), most ET charging stations deployed in the city are exclusively for ETs, which cannot be used by electric private vehicles. As shown in Figure 21, this fast charging station is exclusively for ETs, and we found no private electric vehicles charged in this station when we did the field study there. Even though some charging stations may be shared by private EVs with ETs, few private EVs prefer to utilize fast charging stations for the following two reasons. (i) EVs used for commuting have no needs to leverage fast charging like commercial ETs, which rely on

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Fig. 21. A fast charging station exclusively for electric taxis.



Fig. 22. A public fast charging station.

the fast charging stations to keep the normal business activities, so private EV drivers prefer to charge their cars at home in the evening when the electricity price is also lower than the daytime price. (ii) A fast charging mode can accelerate the degradation of the battery, so private EV drivers usually would not use fast charging stations except in emergency circumstances. We also verify this during the field studies in Shenzhen. Figure 22 shows an example of the status of a public fast charging station, and we found less than 10% of all charging points are utilized by private electric vehicles. Based on this, we consider that other EVs have little influence on the charging recommendation. Hence, in this paper, we envision that all fast charging stations are exclusive for ETs, which is also adopted by some other related research [16, 25, 38].

In this paper, we are working with the city government and we try to improve the overall charging efficiency of all ETs in the city. Hence, the fleet here includes all ETs in the city instead of taxis of a specific company. In addition, we can also consider some uncertainties (e.g., competition of the vehicles from other companies) to assume that all vehicles from other companies will not follow our recommendation, which is implicitly included in Figure 18, i.e., the impact of different recommendation following rates.

Impact of Scales of ETs. Even though most cities in the world do not have ETs as many as 13,000 and Shenzhen is the only city that has such a large-scale and all ET fleet, we argue that our method still works for other cities because our method relies on only the drivers' mobility and charging instead of city features, but the real-world performance will be impacted by the number of ETs and available charging resources in the city. For example, when the ET fleet size is not too large and there are relatively enough chargers in the city, the queuing phenomenon will not be severe, so the original charging time of ETs will also be small and it is challenging to decrease it too much. When there are more and more ETs, while the charging resources cannot keep pace with its increase, the competition between ETs for charging resources will become fierce, which leads to a much longer charging queuing time, so our fleet-oriented charging recommendation system can significantly improve the overall charging efficiency. To summarize, our ForETaxi can achieve better performance than other methods under a different number of ETs, and the performance will be more significant when the charging resource competition is more fierce.

Impact of Vehicle Model. In our work, all EVs are the same model, i.e., BYD e6, and they have the same battery consumption model and charging model, so they share the same solution. For different EV models, they have different battery capacities, consumption rates, and charging rates, which will impact their charging service time as shown in Equations (1)–(3). The traveling time will not be influenced as shown in Section 4.3, but the queuing time will be different if EVs have different charging rates. As shown in Equation (6), our solution considers the charging time (traveling time, queuing time, and service time) of individual EVs, so different EV models will not impact our solution since we will input the traveling time, queuing time, and service time of individual EV to our model for decision making. If there are different EV models, we only need to specify their battery capacities, consumption rates, and charging rates in Equations (1)–(3) to calculate the traveling time, queuing time, and service time of individual EVs to feed into our optimization objective.

7 CONCLUSION

In this paper, we design a data-driven fleet-oriented charging recommendation system called ForE-Taxi based on multi-source sensor data with real-time charging resource allocation, which aims to obtain an optimal charging recommendation for the entire fleet, instead of individual vehicles. ForETaxi considers different practical factors for recommendation including charging queuing time, service time, possible future charging demand and passenger demand, and so on. Real-world sensor data including GPS data, taxi transaction data from more than 13,000 ETs, road network data, and all ET charging stations in Shenzhen are used to verify the performance of the ForETaxi. Extensive results show that our ForETaxi outperforms other state-of-art methods by about 16% of the total charging time reduction and 82% of the queuing time reduction.

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