FairCharge: A Data-Driven Fairness-Aware Charging Recommendation System for Large-Scale Electric Taxi Fleets

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Our society is witnessing a rapid taxi electrification process. Compared to conventional gas taxis, a key drawback of electric taxis is their prolonged charging time, which potentially reduces drivers' daily operation time and income. In addition, insufficient charging stations, intensive charging peaks, and heuristic-based charging station choice of drivers also significantly decrease the charging efficiency of electric taxi charging networks. To improve the charging efficiency (e.g., reduce queuing time in stations) of electric taxi charging networks, in this paper, we design a fairness-aware Pareto efficient charging recommendation system called FairCharge, which aims to minimize the total charging idle time (traveling time + queuing time) in a fleet-oriented fashion combined with fairness constraints. Different from existing works, FairCharge considers fairness as a constraint to potentially achieve long-term social benefits. In addition, our FairCharge considers not only current charging requests, but also possible charging requests of other nearby electric taxis in a near-future duration. More importantly, we simulate and evaluate FairCharge with real-world streaming data from the Chinese city Shenzhen, including GPS data and transaction data from more than 16,400 electric taxis, coupled with the data of 117 charging stations, which constitute, to our knowledge, the largest electric taxi network in the world. The extensive experimental results show that our fairness-aware FairCharge effectively reduces queuing time and idle time of the Shenzhen electric taxi fleet by 80.2% and 67.7%, simultaneously.

CCS Concepts: • **Human-centered computing** → *Ubiquitous and mobile computing*; • **Information systems** → *Spatial-temporal systems.*

Additional Key Words and Phrases: Electric taxi; fairness-aware; Pareto efficiency; charging recommendation; recommendation system

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1 INTRODUCTION

As an important urban transport mode, taxis are essential for people's daily activities [46]. Nevertheless, taxis typically have high gas consumption and emissions due to their long-time daily operations, e.g., around-the-clock, which inevitably brings significant challenges to the sustainable development of cities [53]. Compared to conventional gas taxis, electric taxis (ET) show considerable advantages in terms of energy consumption and emissions, e.g., zero tailpipe emissions of ETs, which motivate many city governments (e.g., Beijing, Chinese city Shenzhen, and New York City [32, 33]) to promote large-scale ET fleets. For example, it is expected that all gas taxis in Shenzhen will be replaced by ETs by the end of 2019, leading to the largest all-ET network in the world [24]. Similarly, New York City has the initiative to replace one-third of its gas taxis with ETs by 2020 [5].

However, despite their advantages of energy-saving and environmentally friendly nature, ETs currently have not been adopted worldwide due to several reasons, e.g., low cruising range (e.g., less than 250 km), high prices (e.g., over $45,000), and, most importantly, complicated charging problems. Among these issues, charging is the key concern that hinders the ETs to release their full potential [16, 34, 37]. In particular, charging of large-scale ET fleets is extremely challenging considering their unique characteristics. (i) **High charging frequency.** Due to the limited battery capacity, ETs have a lower cruising range compared to gas taxis, which means that they need to charge multiple times per day, given their long daily operation time and distance. For example, in Shenzhen, it is very common for an ET to charge more than twice per day [3]. (ii) **Long charging duration.** A charging activity of ETs typically lasts for half an hour to two hours, even using fast charging, which potentially reduces their daily operation time and distance [34]. (iii) **Intensive charging peaks.** Besides, the intensive charging activities in some periods (e.g., 3:00-5:00 and 12:00-13:00) also cause charging peaks and long queuing phenomena in these periods [30]. Moreover, due to *high costs*, *security concerns* [31], and *inaccessible land resources* for extra charging infrastructures, the numbers of charging stations and charging points in a city are generally limited and insufficient compared to gas stations, which leads to charging resource competition and prolonged queuing time in charging stations. A combination of the above charging demand (e.g., charging frequency, duration, and peaks) and charging supply issues makes the current charging problem very challenging.

Many researchers have made efforts towards the challenging ET charging problem [3, 14, 16, 19, 30]. However, most existing works [16, 42, 43] focus on how to build more charging stations to satisfy charging demand, which is potentially costly and impractical in some cities. There are also some research efforts trying to design charging recommendation systems [30, 35] to reduce charging overhead of ETs. Although these works achieved good performance when the overall objective of recommendation is to maximize the profits of taxi companies, **the individual fairness between ET drivers was not considered**. However, in this paper, we argue that a recommendation not considering the fairness of individual drivers might not be practical in some real-world settings where the profit model of taxi drivers is largely decided by their individual service performance instead of the performance of the overall systems, e.g., Shenzhen and Beijing taxi networks [34, 53]. As a result, the drivers may not have the incentive to follow the recommendation [35] if the recommendation decisions for them are unfair, which will impair the system performance in the long run [39]. Thus, we aim to address the key drawback of existing works with a fairness-aware charging recommendation. To achieve this goal, the key technical challenge is how to consider the fairness for the ET charging scenario and find the fairness-aware optimal solution recommendation for a large-scale fleet in real time.

In this paper, we advance the existing state-of-the-art works by asking a different question: *can we recommend a fleet of ETs to charge and achieve an optimal solution with fairness as a constraint? Which means that the overall charging efficiency of all ETs with current or near-future charging requests is jointly optimized, and the extra charging idle time is under a certain threshold for all ET drivers even though prolonged.* To answer this question, we perform a data-driven study to design a fairness-aware charging recommendation system called FairCharge to improve the overall charging efficiency of large-scale ET networks based on fairness constrained Pareto optimization. The main advantage of FairCharge is that it considers fairness as a constraint when making Pareto efficient recommendations, which is the key difference between our work and existing works. FairCharge makes recommendation decisions considering not only the status of the current ET charging request but also the status in a near-future duration of other relevant ETs in the fleet, which also has not been considered in previous individual-based recommendations [30, 35].

To make our design more practical, we also consider some real-world factors for charging recommendations. According to NYC Taxi & Limousine Commission [2], an ideal ET program should cause minimal disruption to the taxi industry since the taxi industry has chosen its many current practices based on years of experiences and learning about what works well and what does not work well in a real-world setting. If we change the time when they send requests or when they go to charging stations, it may affect the entire taxi system and possibly change drivers' daily life, e.g., the arranged time conflicts with drivers' daily schedule, resulting in not following our recommendation. Therefore, in this paper, we only recommend ET drivers to the corresponding charging stations when they send charging requests for practical considerations.

Specifically, the key contributions of this paper include:

- To our knowledge, we conduct the first fairness-aware ET charging recommendation research based on large-scale real-world ET data, i.e., more than 16,400 ETs and 117 charging stations. Such a large-scale and citywide study has the potential to advance our understanding of ET charging patterns in a practical setting where fairness is a key concern, which is challenging to be discovered by simulated data-based studies.
- We design a fairness-aware charging recommendation system called FairCharge, which aims to improve the overall charging efficiency of ET networks (e.g., reducing the idle time) based on the Pareto optimality and fairness constraints. We first formulate the ET charging recommendation problem as a fairness constrained Pareto optimization problem, and then we leverage Pareto improvement to find the optimal solution.
- We design a context-aware model to calculate the traveling time at road segment levels, which is used to estimate the traveling time from charging request locations of each ET to any charging stations. We also provide a fleet-oriented optimal queuing inference algorithm to calculate the queuing time in stations. Finally, we integrate all obtained information into the fairness constrained Pareto efficient charging recommendation system for a fairness-aware optimal solution by Pareto improvement.
- More importantly, we implement and extensively evaluate FairCharge based on real-world data from Shenzhen, including GPS records and transaction records from more than 16,400 ETs. The simulation results show our FairCharge reduces 80.2% of the queuing time and 67.7% of the idle time, simultaneously.

The rest of the paper is organized as follows. Section 2 introduces the information of existing taxi infrastructure and generated data. Section 3 shows our design motivation. Section 4 describes the detailed FairCharge modeling and system design. Section 5 evaluates FairCharge with real-world datasets and shows comparisons with state-of-the-art recommendation methods. Some discussions and lesson learned are shown in Section 6, followed by related work in Section 7. Finally, we conclude this paper in Section 8.

2 DATA DESCRIPTION

In this section, we first introduce the current ET infrastructure in Shenzhen, and then we show the multi-source data generated from it. Finally, we visualize the ET activities and charging stations.

2.1 ET Infrastructure

The Chinese city Shenzhen has, to our knowledge, the largest ET fleet in the world, including 16,407 ETs in October 2018, accounting for more than 80% of its all taxis. During this project, we are working with the Shenzhen

Transportation Committee, and we aim to design a charging recommendation system for effective charging management of the city.

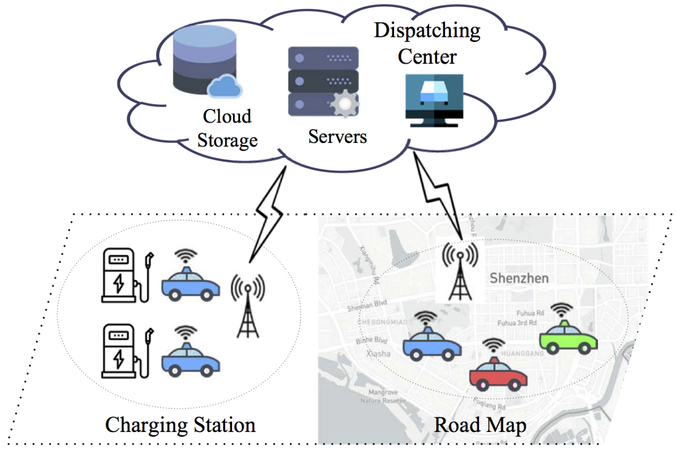

Fig. 1. Current taxi infrastructure in Shenzhen.

There are two types of taxis in Shenzhen, i.e., conventional gas taxis (red and green color) and new electric taxis (blue color). Except for the basic taximeters, all taxis in Shenzhen are equipped with GPS and communication devices. The existing taxi infrastructure in Shenzhen can be described as Figure 1. Dispatching centers are built by the transportation committee to monitor the operating status of all taxis, and all GPS data are uploaded periodically to dispatching centers through cellular networks. Charging stations with fast charging points are deployed to charge the Shenzhen ET fleet for their daily operation.

2.2 Multi-Source Heterogeneous Data

In this infrastructure, multi-source heterogeneous data were collected for monitoring, accounting, and management purposes:

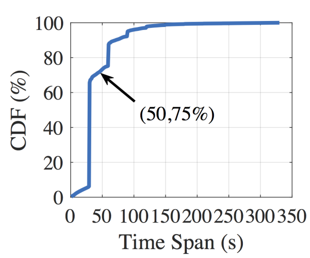

Fig. 2. GPS record granularity.

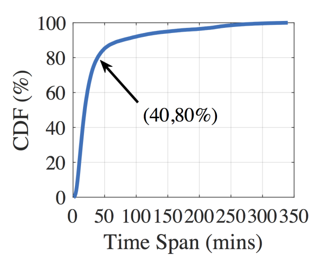

Fig. 3. Transaction granularity.

(i) With GPS devices, both static attributes (e.g., vehicle IDs) and dynamic attributes (e.g., real-time longitudes and latitudes, timestamps, speeds, and passenger load indicators) are recorded. The cumulative distribution function (CDF) of GPS record uploading intervals is shown in Figure 2. We found that 70% of GPS records were uploaded every 30 to 50 seconds, and 75% of GPS records were uploaded within every 50 seconds, leading to a detailed physical status log.

(ii) With taximeters, the following information of each trip was recorded for accounting: the vehicle ID, pickup and drop-off timestamps, operating distances, cruising distances, and fares. The CDF of the transaction record uploading gap of each taxi is shown in Figure 3. We found that 80% of ET transaction records were uploaded shorter than every 40 minutes, leading to a detailed trip-level status log.

(iii) With sensing and communication devices, both static and dynamic attributes are uploaded periodically to dispatching centers via cell towers, and then the massive GPS data is stored in cloud servers of dispatching centers for management and analyses.

(iv) Each charging station metadata has a station ID, a station name, longitude, latitude, and the number of charging points in it. There are 117 fast charging stations deployed in Shenzhen for ETs in 2018. The detailed distribution of charging stations will be shown in Section 2.3.

(v) We also leverage the road segment data of Shenzhen for a fine-grained charging modeling. In total, there are about 135 thousand road segments and 87 thousand road intersections in Shenzhen. Each road segment has a road ID, road name, start longitude and latitude, end longitude and latitude, road length, etc.

Table 1. Examples of the datasets.

Taxi GPS	plateID	longitude	latitude	time	speed(km/h)
	YBDXXXXX	113.928185	22.681187	2018-10-14 05:40:31	21
Taxi Transaction	plateID	pickup time	dropoff time	cost(CNY)	distance(m)
	YBXXXXX	2015-06-20 07:02:29	2015-06-20 07:18:29	43.6	15398
Charging Station	stationID	stationName	longitude	latitude	# of charging points
	53	LGS0012	114.0705118	22.65589517	52
Road Network	roadID	startLongitude	startLatitude	endLongitude	endLatitude
	27813	114.426971	22.604326	114.4370363	22.5904528

In total, our dataset includes 5-year (2014-2018) ET data in Shenzhen, which includes over 2 TB GPS records and 56 GB transaction records of more than 16,000 ETs, combined with data of 117 charging stations. An example of the dataset is shown in Table 1.

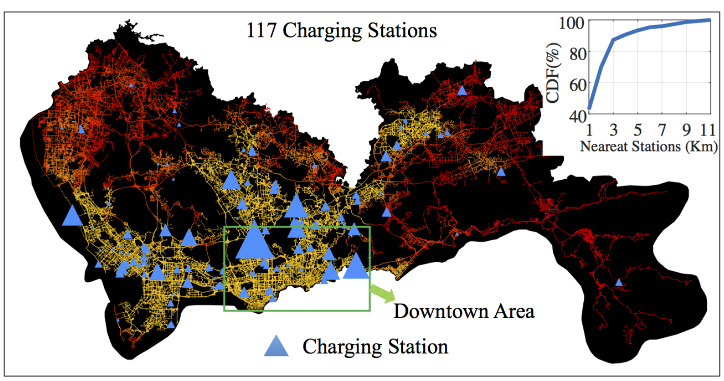

Fig. 4. ET activities and charging stations.

2.3 ET Activities and Charging Station Visualization

Figure 4 shows a visualization of charging station distribution and ET activity distribution in 2018. The yellow (i.e., light) areas mean there are higher ET activities in these locations, and the red (i.e., dark) areas indicate lower ET visiting frequencies. The blue triangles stand for charging stations, and the sizes of triangles stand for the sizes of the charging stations, i.e., a large triangle means a large charging station with more charging points. Considering both charging station distribution and ET activity distribution, we found that places with high ET activities are also the locations with more charging stations and charging points, which indicates a correlation between charging stations and ET activities. The upper right corner shows the CDF of the distance between each charging station and its nearest charging station, which indicates whether there are other nearby choices when there are no charging points available in the current station. We found about 90% of charging stations have at least one neighbor within 3 km, which indicates most charging stations in Shenzhen are well-connected, so a recommendation system can easily find another near station for an ET if there are no available charging points in its dedicated charging station.

3 MOTIVATION

In this section, we first describe the charging process of ETs with three stages, followed by our data-driven observations, e.g., charging spatial & temporal patterns. Finally, we show the key idea of our FairCharge.

3.1 Charging Process of ETs

Figure 5 shows a charging process of ETs.

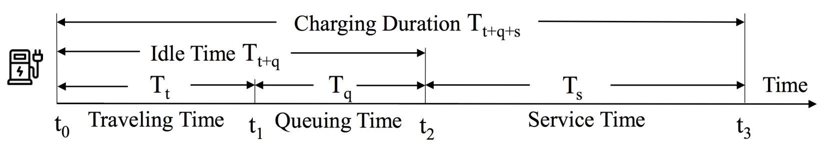

Fig. 5. A charging process of ETs.

(i) At time t_0, an ET has a charging request, and it travels to a charging station at t_1, so we define the time duration $T_t = t_1 - t_0$ as the **traveling time**. (Note that in the current situation, ET drivers make charging decisions by themselves, which means they choose when and where to charge based on their experiences.)

(ii) When the ET arrives at a charging station at t_1, all charging points may be occupied, so it queues for an available charging point to t_2, and we define $T_q = t_2 - t_1$ as the **queuing time**. $T_q = 0$ if there are available charging points for the ET when it arrives to the charging station.

(iii) At time t_2, the ET starts the charging service and finishes it by t_3. Then, the time duration between t_2 to t_3 is defined as the **service time**, which is $T_s = t_3 - t_2$.

(iv) Due to different charging station choices would not have a large impact on the service time [30, 34, 35], so our key concern is $T_t + T_q$, which is defined as the **idle time** T_{t+q} since the ET neither serves passengers nor under charging services.

(v) The **charging duration** of a whole charging event is $T_{t+q+s} = t_3 - t_0 = T_t + T_q + T_s$.

3.2 Data-Driven Observations

Based on our data-driven charging pattern analysis, we provide the following observations:

(i) There is an unbalanced spatial and temporal charging pattern. For the unbalanced spatial pattern, 62% of charging events happen in 23 (i.e., 20%) charging stations, as shown in Figure 6. For the unbalanced temporal pattern, there are three distinct charging peaks (e.g., 2:00-6:00, 12:00-13:00, and 16:00-18:00 as shown in Figure 7), resulting in some charging stations are overcrowded during these time periods, which potentially prolong the queuing time at charging stations. We also verify this long queuing phenomenon through a set of field studies. More details will be shown in Section 5.1.

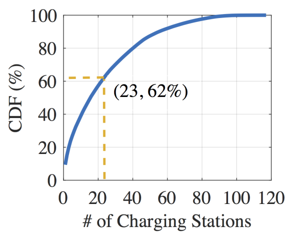

Fig. 6. Charging spatial distribution.

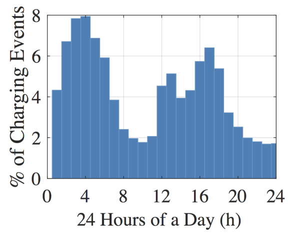

Fig. 7. Charging temporal distribution.

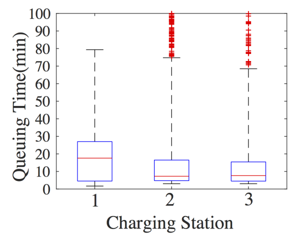

Fig. 8. Queuing time in top 3 stations with most charges.

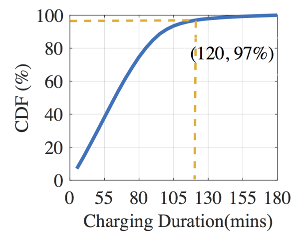

Fig. 9. Charging duration distribution.

(ii) Based on our data-driven analyses and field studies, we found that ET drivers tend to charge in downtown areas, especially for large stations with more charging points in there. This heuristic charging station searching strategy potentially prolongs their queuing time in these stations. For example, Figure 8 shows the queuing time in three charging stations with the most charging events during 12:00-14:00. We found that most ETs need to wait more than 10 minutes for available charging points, and some ETs need to wait more than an hour. Such a long queuing time severely reduce the charging efficiency of the ET charging network.

(iii) The charging duration of 97% of charging events would last for half an hour to two hours, as shown in Figure 9, which potentially results in operation time and operation distance reduction of ETs. However, for ET drivers, what they care about is their profits, and a long time for charging activities will make them unsatisfactory, so they wish their idle time can be reduced if current battery technologies cannot be improved shortly.

From our data-driven observations, we argue it is necessary for us to develop a better charging station deployment strategy or design an effective charging recommendation system to address these inefficient charging issues. However, it is challenging to deploy abundant charging stations for ETs due to some real-world constraints, e.g., unavailable and costly land resources [34]. In addition, even though with enough charging resources, the heuristic charging behaviors of ET drivers and intensive charging peaks in some periods will also decrease the charging efficiency of the whole ET fleet. As a result, in this paper, we aim to design a charging recommendation system to improve the charging efficiency of the whole ET charging network with the fairness constraint for the long-term benefit, which is more economically efficient and feasible compared to deploy additional charging stations and unfair recommendation strategies.

3.3 Key Idea of FairCharge

The key idea of our FairCharge recommendation is that we try to minimize the maximum prolonged idle time for all drivers that send charging requests in a period compared to their utopia recommendation decisions, which intuitively means that the worst case for each driver is not too bad. We consider all potential charging requests in a short near future period τ, and then we recommend all of these ETs to achieve the fairness constrained Pareto efficiency. Even though the key idea seems not too complicated, it is nontrivial to have a suitable fairness definition for the ET charging scenario, and it is also not easy to formulate this problem into an existing optimization framework, especially for a large-scale citywide number of ETs, which is also challenging to find an effective charging management approach in real-world scenarios.

As shown in Figure 10, there are two charging stations (i.e., S_1 and S_2) and there are two ETs (i.e., ET_1 and ET_2). The letters labeled near each line stand for the time (minutes) that each ET needs to spend for obtaining an available charging point in each station, i.e., *traveling time* + *queuing time*. We give an example to explain the key idea of FairCharge. Suppose $\tau_1 = 10$, $\tau_2 = 10$, $\tau_3 = 10$, and $\tau_4 = 20$, and there is an available charging point in each charging station. For an individual-oriented recommendation system, it adopts a *first request first served* policy [30]. If ET_1 sends a charging request first, it will be recommended to S_1 by the system. At this time, if ET_2 requests a recommendation, the system will recommend it to S_2, resulting in 30 minutes of the total *idle time* for the two ETs. But if we consider the status of all ETs in the fleet and consider requests in the near future, we predict the request from ET_2, so we can recommend ET_1 to S_2 and ET_2 to S_1 to obtain a global optimum with 20 minutes' *idle time*. In this case, the fleet information (e.g., the future charging requests and status of other ETs) has not been considered in the individual-oriented recommendation, and we can save about 33.3% (10 minutes) of the total *idle time* since we consider it from a fleet-oriented perspective. In this example, $(ET_1(\tau_1), ET_2(\tau_4))$ is an allocation $\mathbf{Q}^1$ and $(ET_1(\tau_2), ET_2(\tau_3))$ is another allocation $\mathbf{Q}^2$. The process from $\mathbf{Q}^1$ to $\mathbf{Q}^2$ is a Pareto improvement since $\mathbf{Q}^2$ reduces the overall charging time of the two ETs without hurting any other ETs. We found the Pareto improvement is a common case in our FairCharge charging recommendation scenario.

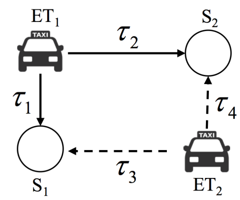

Fig. 10. Charging scenarios of ETs.

In another case, if $\tau_1 = 6$, $\tau_2 = 16$, $\tau_3 = 7$, and $\tau_4 = 18$, then both allocation $\mathbf{Q}^1$ (i.e., $ET_1(\tau_1)$, $ET_2(\tau_4)$) and allocation $\mathbf{Q}^2$ (i.e, $ET_1(\tau_2)$, $ET_2(\tau_3)$) are Pareto efficient. Given our fairness constraint, our recommendation system selects $\mathbf{Q}^2$ since $ET_2(\tau_4)$ - $ET_2(\tau_3)$=11 is larger than $ET_1(\tau_2)$ - $ET_1(\tau_1)$=10, so we try to make our recommendation decisions fairer and more acceptable by all drivers.

To make the FairCharge efficient, we need to have enough charging events happening in the time duration τ (e.g., one minute), so we made a data-driven observation. As shown in Figure 11, we found that there were more than 10 charging events per minute in 75% of the time of a day, which indicates that it has the potential for us to leverage the Pareto efficiency to achieve the optimal charging recommendation even making recommendation decisions in a short duration (e.g., one minute). Hence, with this solid established economic theory, combined with our data-driven charging pattern investigation of ETs, we design a data-driven fairness-aware charging recommendation system based on Pareto efficiency to achieve the optimal charging efficiency for the whole ET charging network.

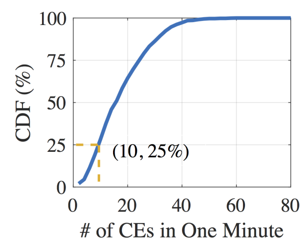

Fig. 11. CDF of charging events in one minute.

Summary: To our knowledge, existing charging recommendation research rarely consider if their decisions are Pareto efficient or not, and also they seldom consider charging recommendation from the fairness perspective, where the benefits of different ET drivers may be mutually correlated, and we need to make sure the worst possible decisions for some drivers are still acceptable (e.g., idle time is under a certain threshold). To make the charging recommendation fairer and attract more drivers to follow it, we consider fairness as a constraint when making recommendation decisions in this paper. Even though the definition of fairness in different scenarios is different [1], we carefully define the fairness definition in the ET charging scenario based on their charging patterns, which will be shown in Section 4.1.

4 SYSTEM MODELING AND DESIGN

In this section, we show the detailed modeling and design processes of our FairCharge recommendation system. (i) We introduce the Pareto efficient charging recommendation, which includes the real-time charging problem formulation and Pareto improvement. (ii) A context-aware traveling time model at the road segment level is presented to calculate the *traveling time*, and a fleet-oriented queuing algorithm is proposed to infer *queuing time* of each charging event based on the status of all relevant ETs in the fleet. (iii) All previously-obtained information is fed to Pareto improvements for the charging recommendation.

4.1 Real-Time Charging Problem Formulation

In this paper, we formulate the real-time charging recommendation problem as an online Dynamic Resource Allocation (DRA) problem [15], which allocates ETs that have charging requests to charging stations to achieve the Pareto efficiency. Pareto efficiency (optimality) [50] means that no one can gain further benefits without making at least one individual worse off, named after one of the pioneers of Microeconomics Vilfredo Pareto [22]. Pareto efficiency is a formally defined concept for determining if an allocation is optimal or not.

Suppose there is an ET fleet with N ETs $\{ET_1, ET_2, \cdots, ET_N\}$ in a city, and the ET fleet sporadically generates m charging events $\{e_1, e_2, \cdots, e_m\}$ in a short duration τ. To keep the daily operation of the ET fleet, there are n charging stations $\{s_1, s_2, \cdots, s_n\}$ deployed across the city, and the number of charging points in each charging station constitute a vector $\mathbf{p} = [p_1, p_2, \cdots, p_n]^\intercal$. In the following part, we will utilize $1 \le i \le m$ and $1 \le j \le n$ to index the charging events and charging stations, respectively.

The Real-Time Charging Recommendation (RTCR) [30] problem aims to find a **time-varying** online *allocation matrix* $\mathbf{Q} = [Q_{ij}]_{m\times n}$ to optimize the charging efficiency of the ET fleet in real time, where $Q_{ij} \ge 0$ means whether the charging event e_i is recommended to s_j or not, e.g., $Q_{ij} = 1$ if e_i is recommended to s_j, otherwise $Q_{ij} = 0$. A Pareto efficient charging recommendation attempts to provide recommendations according to the Pareto efficient allocation of the charging points regarding each ET driver's benefits (e.g., idle time). Let $\mathbf{Q}_i$ be the allocation vector for event e_i, so we have $\mathbf{Q} = [\mathbf{Q}_1, \mathbf{Q}_2, \cdots, \mathbf{Q}_m]^\intercal$ for all charging events. Since one charging event can be only recommended to one charging station, the allocation $\mathbf{Q}_i$ should be a unit vector $\mathbf{u}_i$, which means that it only includes a single 1. We take $T_i(\mathbf{Q}_i)$ as the idle time that charging event e_i spends for its allocated charging station, which is the sum of the *traveling time* and *queuing time*. Therefore, the charging recommendation for m charging events in a short duration can be formulated as the following Pareto optimization problem,

$$\begin{aligned} \underset{Q=[Q_{ij}]_{m\times n}}{\text{minimize}}\ & \mathbf{T}(\mathbf{Q}) = [T_1(\mathbf{Q}_1), T_2(\mathbf{Q}_2), \cdots, T_m(\mathbf{Q}_m)]^\intercal \\ s.t.\ & \mathbf{Q}_i = \mathbf{u}_i,\ \|\mathbf{Q}_i\| = 1,\ \forall i = 1, 2, \cdots, m \end{aligned} \tag{1}$$

which minimizes the idle time of all charging events in a short duration (e.g., 1 minute) jointly. This model produces Pareto efficient allocations on idle time of all charging events, which are then taken for recommendation decisions to achieve the optimal recommendation. After a round of recommendation, the FairCharge system will update the information of all ETs and stations (e.g., current locations, charging station status, number of queuing ETs in each station, etc). Then based on the newly updated data and newly received charging requests, FairCharge dynamically makes new recommendation decisions in an **online manner**, i.e., continuously update the allocation matrix $\mathbf{Q}$.

4.2 Pareto Efficiency and Fairness

Different from single-objective optimization, there are typically a set of feasible solutions for a Pareto optimization problem. In addition, the objective functions $T_i(\mathbf{Q}_i)$ in the above Pareto optimization problem are usually mutually correlated, which means that decreasing the idle time of one ET driver may increase the idle time of other ET drivers. As a result, given a Pareto optimization problem, we are usually interested in its Pareto efficient solutions (i.e., Pareto efficiency), with which we can achieve the optimal charging recommendation.

Definition 4.1. Pareto Efficient: A feasible recommendation $\mathbf{Q}^*$ is *Pareto efficient* iff there does not exist another feasible recommendation $\mathbf{Q}$, such that $\mathbf{T}(\mathbf{Q}) \le \mathbf{T}(\mathbf{Q}^*)$ with at least one $T_i(\mathbf{Q}) < T_i(\mathbf{Q}^*)$. Otherwise, $\mathbf{Q}^*$ is *Pareto inefficient*.

Definition 4.2. Pareto Frontier: The set of all Pareto efficient solutions is called the *Pareto frontier*.

Definition 4.3. Pareto Improvement: *Pareto improvement* is the approach to achieve the Pareto efficiency. A change from status $\mathbf{Q}^1$ to $\mathbf{Q}^2$ is called a Pareto improvement iff $\mathbf{T}(\mathbf{Q}^2) \leq \mathbf{T}(\mathbf{Q}^1)$ with at least one $T_i(\mathbf{Q}^2) < T_i(\mathbf{Q}^1)$.

Definition 4.4. Utopia Recommendation: A recommendation $\mathbf{Q}^\circ \in \mathbb{R}^n$ is a *utopia recommendation* iff $T_i(\mathbf{Q}^\circ) = \min_{\mathbf{Q}} T_i(\mathbf{Q})$ for each $i = 1, 2, \cdots, m$. A corresponding decision variable $\mathbf{Q}_i^\circ \in \mathbb{R}^n$ is a utopia decision variable.

Intuitively, a Pareto improvement is an action conducted in the recommendation system that harms no ET drivers and reduces the idle time of at least one ET driver. The Pareto improvements can be increasingly made one by one until the system achieves a Pareto efficiency, at which status no more Pareto improvement can be made [20]. A utopia recommendation (or *ideal recommendation*) is an ideal solution to the charging Pareto optimization problem, but usually, it is impossible to find a solution that includes utopia recommendations for all ETs.

In this paper, we try to balance the "selfish" charging behaviors of drivers and myopic optimization of operators. For ET drivers, they expect their idle time as short as possible so that they can have a longer time for the operation. While for taxi operators, they usually try to minimize the cumulative idle time across the entire fleet to obtain temporary global benefits, which may severely damage some drivers' benefits, e.g., prolonging the idle time a lot for some drivers. This short-term optimization may result in low participation rates of drivers from a long-term perspective, which, in turn, makes the system inefficient. Hence, if a recommendation system needs to operate in the long-run, it should be fair, which means it needs to attract more ET drivers to participate it stably, so it is necessary for drivers to feel they are fairly treated, e.g., the idle time is acceptable even though they are recommended to suboptimal charging stations.

Definition 4.5. Fairness Recommendation: A recommendation $\mathbf{Q}^f \in \mathbb{R}^n$ is a *fairness recommendation* if $\mathbf{Q}^f = \underset{\mathbf{Q}}{\operatorname{argmin}}\{\max_i\{T_i(\mathbf{Q_i}) - T_i(\mathbf{Q_i}^\circ)\}\}$ for each $i = 1, 2, \cdots, m$, which means that the maximum prolonged time for all drivers that send charging requests in a period should be minimized compared to their utopia decisions, which intuitively means that the worst case for each driver is not too bad. This fairness definition potentially makes the recommendation decisions acceptable to drivers even though some ETs' idle time may be prolonged.

It should be noted that the definition of fairness is not unique, and it even subjectively depends on the system designers. In this work, we take the "least misery" [39] definition of fairness as our design guideline after exploring many existing fairness related works [1, 12, 39, 50], which we believe best matches the driver incentives, to show how this fairness consideration effectively helps real-time charging recommendation.

By integrating fairness constraints into the Pareto optimization problem in equation (1), we obtain a fairness-aware constrained optimization, which guarantees both the Pareto efficiency and fairness among drivers. The fairness-aware recommendation is formulated as equation (2), where the last constraint guarantees recommendations for all charging events are fair, and $\mathbf{Q_i}^\circ$ is the utopia recommendation for the charging event e_i.

$$\begin{aligned} \underset{Q=[Q_{ij}]_{m\times n}}{\text{minimize}}\ & \mathbf{T}(\mathbf{Q}) = [T_1(\mathbf{Q}_1), T_2(\mathbf{Q}_2), \cdots, T_m(\mathbf{Q}_m)]^\intercal \\ s.t.\ & \mathbf{Q}_i = \mathbf{u}_i,\ \|\mathbf{Q}_i\| = 1,\ \forall i = 1, 2, \cdots, m \\ & \mathbf{Q}^f = \underset{\mathbf{Q}}{\operatorname{argmin}}\{\max_i\{T_i(\mathbf{Q_i}) - T_i(\mathbf{Q_i}^\circ)\}\} \end{aligned} \tag{2}$$

In classical economics, three are three conditions for Pareto Optimality [22], i.e., (i) efficiency in exchange, (ii) efficiency in production, and (iii) efficiency in exchange and production (product mix). Our solution satisfies the three conditions. For the first one, since our solution is obtained based on the "least misery" constraint, which means that the worst recommendation for all ET drivers is still good enough for them to accept, as a result, there is no incentive for them to reject our recommendation and switch to other stations, which result in efficiency in exchange. For the second condition, since all ET drivers who send charging requests in each recommendation round are recommended to charging stations, it means that all production resources are employed. For the last condition, since the charging points in different charging stations have the same charging rates, and all charging points in the same charging station are also equivalent, it means that all charging points have the same marginal rate of substitution. As a result, the third condition is also satisfied. Hence, our problem can reach Pareto efficiency.

In following parts, we introduce how to calculate idle time $T_i(\mathbf{Q}_i)$ of each charging event e_i, which is the sum of *traveling time* T_t and *queuing time* T_q. Then all obtained information is leveraged for charging recommendation.

4.3 Context-Aware Traveling Time Calculation

The location when an ET driver sends a charging request could potentially be any place in the city, which results in the routes to charging stations of ETs may not appear before, so it is necessary to estimate the speed on each road and then estimate the time from any place to each charging station. Hence, in this subsection, we present a context-aware traveling time model at road segment levels to calculate the *traveling time* of each ET to each charging station.

A road network can be seen as a graph consisting of road segments and intersections. The road segments are edges of the graph. The intersections and endpoints of the road segments are the vertices of the graph. The traveling speed on each road segment can be seen as the weight of the edge. According to existing research [9, 25, 40], the traffic conditions of road segments on the same day of different weeks typically are similar, which can be predicted using historical data. Hence, we estimate the average speed of each road segment in different time slots of different days. According to previous research [6, 26, 47], traffic conditions in 5 minutes are typically similar, and the 5-minute partition has been adopted by many previous research [48], so we also select 5 minutes as our time slot length to update the estimation value of traveling time (not for the recommendation). 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 $G = (V, E)$, where $V = \{V_1, V_2, \cdots, V_m\}$ and $E = \{E_1, E_2, \cdots, E_n\}$. We denote the average speed on road segment E_i during time slot τ as $v(\tau, E_i)$, where E_i denotes the road segment from intersection V_i to intersection V_{i+1}. Thus, a speed matrix for time slot τ is obtained, which includes the speed on each road segment of a city during this time slot.

After obtaining the average speed of each road segment, we estimate the *traveling time* between any charging request location (lon_r, lat_r) and charging station location (lon_{s_j}, lat_{s_j}) using the following formula:

$$T_t\left(D_w, lon_r, lat_r, lon_{s_j}, lat_{s_j}\right) = \sum_{i=0}^{k} \frac{L\left(lon_{V_i}, lat_{V_i}, lon_{V_{i+1}}, lon_{V_{i+1}}\right)}{v\left(D_w, \tau, E_i\right)} \tag{3}$$

Where k is the number of road segments between an original location (i.e., the location when a driver sent a charging request (lon_r, lat_r)) and a destination location (i.e., the location of a charging station (lon_{s_j}, lat_{s_j})); D_w is the day of week, e.g., Monday; $L(lon_{V_i}, lat_{V_i}, lon_{V_{i+1}}, lon_{V_{i+1}})$ is the length of the road segment between intersection V_i and V_{i+1}, and we set the first intersection as the location where a driver sends a charging request, i.e., $lon_r = lon_{V_0}$ and $lat_r = lat_{V_0}$. We set the last intersection as the location of charging station s_j, i.e., $lon_{s_j} = lon_{V_{k+1}}$ and $lat_{s_j} = lat_{V_{k+1}}$; $v(D_w, \tau, E_i)$ is the average speed of the corresponding road segment E_i during time slot τ of a particular day of week D_w. Thus, the *traveling time* T_t from the current location to each charging station can be obtained for each specific day of a week.

4.4 Fleet-Oriented Queuing Time Calculation

If many ETs arrive at the same charging station nearly the same time, they will compete for limited charging points and then cause long queuing lines in some specific time durations, e.g., 3:00-5:00 and 12:00-13:00 as Figure 7 shows. Hence, reducing the *queuing time* of ETs for available charging points is a key factor in reducing the idle time of them, and it is also one of our objectives.

If an electric taxi ET_x arrives at a charging station at time t_1, the *queuing time* T_q is decided by the number of ETs being served in the station and the number of ETs arrived at this station prior to ET_x. In certain circumstances, when ET_x is going to a charging station, there may be other ETs submitting charging requests at the same time or near future (e.g., as Figure 11 shows), so we can coordinate them for a batch-based solution to avoid long *queuing time* compared to the streaming one-by-one fashion [30, 35].

In summary, if there are available points when ET_x arrives at a station, the *queuing time* would be 0. Otherwise, there exists a *queuing time*, which can be formulated as:

$$T_q = t_2 - t_1 = \begin{cases} 0 & \textit{no queuing} \\ \min\limits_{i \in I}\{t_3^i - t_1\} & \textit{queuing} \end{cases} \tag{4}$$

Where t_1 and t_2 are the time when ET_x arrives a charging station and starts charging service as we defined in Section 3.1; I is the set of ETs served and queuing in the station, and t_3^i stands for the time when ith ET is fully charged and leave, leading to an unoccupied point for ET_x. The time when an ET fully charged and leave is estimated by utilizing a widely used charging model [10, 35]. Based on all the fleet information, we then design the fleet-oriented optimal queuing inference algorithm, which is shown as Algorithm 1. When the $(n_s + n_e - p_j + 1)^{th}$ ETs leave this station, there will be an available charging point for ET_x, so we can obtain the queuing time of ET_x in charging station s_j by this fleet-oriented queuing model.

Algorithm 1: Fleet-Oriented Queuing Inference

Input: A charging station s_j, the number of charging points in it p_j, an ET needed to charge ET_x, and the time it arrives at the station t_1, the number of ETs being served or queuing ahead of ET_x in the station n_s, the number of ETs sending request during the same time slot and arriving early than ET_x is n_e

Output: Queuing time T_q

```
if p_j − n_s − n_e > 0 then
    T_q ← 0
elseif p_j − n_s − n_e ≤ 0 then
    T_q ← min{t_3^(n_s+n_e−p_j+1) − t_1}
return T_q;
```

4.5 Charging Recommendation

Given *traveling time* T_t and *queuing time* T_q we computed in Section 4.3 and 4.4 for each charging event e_i, we obtain the idle time $T_i(\mathbf{Q}_i)$ for each allocation $\mathbf{Q}_i$. The Pareto optimization with the fairness constraint for charging recommendation is shown as Equation 5, and then we leverage effective methods to solve this problem.

$$\begin{aligned} \underset{Q=[Q_{ij}]_{m\times n}}{\text{minimize}}\ & \mathbf{T}(\mathbf{Q}) = [T_1(\mathbf{Q}_1), T_2(\mathbf{Q}_2), \cdots, T_m(\mathbf{Q}_m)]^\intercal \\ s.t.\ \mathbf{Q}_i &= \mathbf{u}_i \\ \|\mathbf{Q}_i\| &= 1 \\ T_i(\mathbf{Q}_i) &\le \hat{T}_i(\mathbf{Q}_i),\ i = 1, 2, \cdots, m \\ \mathbf{Q}^f &= \underset{\mathbf{Q}}{\text{argmin}}\{\max_i\{T_i(\mathbf{Q_i}) - T_i(\mathbf{Q_i}^\circ)\}\} \end{aligned} \tag{5}$$

In Equation 5, m is the number of charging events; n is the number of charging stations; $\mathbf{u}_i$ is an unit vector with values 0 or 1; $1 \leq i \leq m$ and $1 \leq j \leq n$ are indexes of the charging events and charging stations; $\mathbf{Q_i}^\circ$ is the utopia recommendation for the charging event e_i. The first and second constraint guarantees an event can be recommended to only one charging station. The third constraint guarantees the Pareto improvement for a faster solution since it can help to avoid back and forth in the optimization procedure and keeps the solution directly optimized towards the optimal solution.

We adopt the scalarization with greedy algorithm in [39] to address this optimization problem, which is proven to have high efficiency in solving the Pareto efficient optimization problem in the literature [39, 50]. An important advantage of scalarization with greedy algorithm is computational efficiency. Notice that solving an optimization problem can be very time-consuming, especially for some non-convex optimization problems. The basic idea of the scalarization greedy algorithm is that it scalarizes the objectives into a single objective function, and then gradually deals with one request in each iteration and achieves the highest fairness when it is added to the current allocation matrix. The algorithm runs m iterations to generate a final recommendation, so it is more time-efficient.

It should be noted that the solution may fall into local optimum solutions since we utilize the scalarization-based greedy algorithm. However, since we utilize the "least misery" as a constraint (i.e., the last constraint in Equation 5) to find the final solution, as a result, even if the algorithm converges into a local minimum, it will still guarantee that the obtained solution (i.e., recommendation) is good enough for each driver, and all decisions for drivers are acceptable for them, so we believe the obtained local optimal solution does not have a great impact on the effectiveness of the algorithm.

During the Pareto improvement process, we first construct an initial allocation matrix $\hat{\mathbf{Q}}$ based on an individual-based recommendation to obtain the utopia solution for each charging request. Then we construct an initial idle time $\hat{T}_i(\mathbf{Q}_i)$ of charging event e_i. In addition, we leverage the third constraint in Equation 5 to guarantee the Pareto improvements, which means the charging time of a later allocation $\mathbf{Q}$ must be shorter or equal to the counterpart of the previous allocation $\hat{\mathbf{Q}}$, so it can help to avoid back and forth in the optimization procedure and keeps the solution directly optimized towards the optimal solution. In this case, we reduce the computational complexity of this problem, which effectively helps us to address the real-world large-scale requests from ET drivers. The last constraint is a fairness guarantee, which means that we try to make sure all recommendation decisions are fair for ET drivers. The idea is that the maximum prolonged time for all drivers should be minimized compared to their utopia decisions. Finally, we obtain the fairness constrained Pareto efficient solution for the large-scale ET charging recommendation problem in limited time, which satisfies the real-time requirement.

5 EVALUATION

In this section, we conduct extensive experiments to evaluate the performance of our FairCharge by comparing it with the Ground Truth and some state-of-the-art baselines, in terms of (i) *traveling time*, (ii) *queuing time*, (iii) *idle time* (i.e., traveling time + queuing time), and (iv) *charging station occupation rate*. Finally, we also investigate the system performance under different ET drivers' participation rates.

5.1 Evaluation Dataset

Evaluation Data. We utilize a 6-month ET dataset from May 2018 to October 2018 as we introduced in Section 2.2 to conduct the following experiments, which includes GPS and transaction records from over 16,000 ETs, combined with data of 117 charging stations.

Field Study and App Prototype. To investigate the practical charging problems in Shenzhen, we have conducted a series of real-world field studies in this city. Figure 12 (a) and (b) show the service and queuing phenomena in the Shenzhen Baishizhou charging station between 11:30-13:00, where we saw a severe queuing phenomenon in this station. We found ETs queued up at the entrance of the station and then extended to outer of the station, which can effectively avoid the traffic congestion in the charging station, and drivers can also find an available charging point easily if an ET was fully charged and prepared to leave. Most drivers charging in this station said they normally need to wait for more than half an hour to have access to an available charging point during lunchtime, so they were eager to have the issue addressed by an effective charging station recommendation from taxi companies or the transportation committee.

(a) ET Charging Station (b) Long Queuing (c) App Prototype

Fig. 12. Real-world charging and queuing of ETs in Shenzhen and our App prototype.

We are currently designing an App, and the prototype is shown as Figure 12 (c). To convince ET drivers to participate in our recommendation, we have fairness in mind for a transparent recommendation. In addition to the navigation route to the recommended charging station, our App also informs real-time fairness scores in terms of idle time for all participating drivers. Since our design is for city-scale electric taxi drivers and considering city-scale charging infrastructure, we need to ensure all drivers have opportunities to utilize our system, and a small-scale pilot study may not reflect the fairness between drivers. The first edition of the App is almost completed. It is expected the App will be on the market after approval, and we will then conduct a pilot study to verify the proposed method in practice and find some potential pitfalls.

5.2 Experimental Setup

Simulation Setting. One major issue in charging recommendation scenarios is that recommending a charging event will impact future charging events. Hence, we adopt a rolling horizon manner to make the recommendation decisions, which is widely successfully utilized for online ride-sharing order dispatching (e.g., Uber, Lyft, and DiDi) [17, 41, 49] and charging recommendation [30, 35]. The key idea of rolling horizon based methods is to update the status of all ETs and charging stations in an online fashion, e.g., updating the system status after making recommendation decisions in a short duration τ (e.g., one minute in our work). Then the next recommendation decisions will be made based on the updated status. The reasons why we select one minute are threefold. (i) The first one is that the charging requests in a short time are more predictable because of small accumulative errors. (ii) The second reason is that the number of charging requests in a short time is limited, which is easy for the system to find the optimal recommendation and operate in an online fashion. If we consider a longer duration, there would be more charging requests, which requires the recommendation system to have a higher computational capability to handle it. (iii) The third reason is that waiting one minute is acceptable for drivers even we make a batch-based recommendation without predicting future charging requests, which makes our system more flexible. Under this setting, we found the average recommendation time is about 6.3s for each round of recommendation, which may satisfy the requirements of real-time scenarios.

Start Point and End Point of Traveling Time to Charging Stations. According to the previous research [30, 34, 35], ET drivers usually send charging requests after dropping off passengers, and they have also traveled a certain distance since the last charge, which leads them 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 charging. We merge the transaction data collected from the onboard vehicle equipment and GPS data to obtain the start points t_0 based on the fact that the last drop-offs and the followed queuing in charging stations are adjacent and disjoint. The endpoint t_1 of the traveling stage is the time when an ET arrives at a charging station and starts queuing for charging. The time interval between the two points is set to the *traveling time* T_t to a charging station for simulation.

Baselines: To evaluate the performance of our system, we compare our FairCharge with (i) the baseline (Ground Truth) and three other state-of-the-art charging recommendation strategies, i.e., (ii) *OCSD* in [16], which recommends ETs to the nearest charging stations; (iii) *Recommender* in [30], which is the optimal one-by-one charging recommendation. In addition, we also compare FairCharge with (iv) the **unfair** instantaneously optimal **F**leet-**O**riented (i.e., batch-based) **C**harging **R**ecommendation *UnFair-FOCR*, which do not consider fairness impacts on long-term performance; and (v) the **F**leet-**O**riented **C**harging **R**ecommendation considering **L**ong-term performance loss caused by unfairness *UnFair-FOCRL*, which assumes that the unfairly treated drivers will not follow *UnFair-FOCR* in the future. For the recommendation strategies *OCSD* and *Recommender*, they do not consider future possible charging requests. *UnFair-FOCR* does not consider the fairness of recommendation decisions, and *UnFair-FOCRL* is its long-term performance considering the impact of fairness. However, in our FairCharge, we consider both potential future charging requests and fairness constraints.

Evaluation Metrics: The objective of our FairCharge is to improve the charging efficiency of ET networks, which includes two aspects: (i) spatially balancing the uneven charging supply and demand, and (ii) reducing *idle time* for ET fleets. Hence, we utilize the following metrics to measure the system performance, including (i) *reduction of traveling time*, (ii) *reduction of queuing time*, (iii) *reduction of idle time*, and (iv) *charging station occupation rates.*

Definition 5.1. We define the *Percentage Reduction of Traveling Time (PRTT)*, *Percentage Reduction of Queuing Time (PRQT)*, and *Percentage Reduction of Idle Time (PRIT)* to quantify the system performance on time reduction for ET fleets, which are formulated as:

$$PRTT(R) = \frac{T_t(G) - T_t(R)}{T_t(G)} \times 100\% \tag{6}$$

$$PRQT(R) = \frac{Q_t(G) - Q_t(R)}{Q_t(G)} \times 100\% \tag{7}$$

$$PRIT(R) = \frac{I_t(G) - I_t(R)}{I_t(G)} \times 100\% \tag{8}$$

Where $T_t(R)$ is the *traveling time* of recommendation strategy R, which can be *OCSD*, *Recommender*, *UnFair-FOCRL*, *UnFair-FOCR*, or FairCharge; $T_t(G)$ is the *traveling time* of the Ground Truth; $Q_t(R)$ is *queuing time* based on recommendation strategy R; $Q_t(G)$ is the *queuing time* of the Ground Truth; $I_t(R)$ is *idle time* of recommendation strategy R; $I_t(G)$ is the *idle time* of the Ground Truth.

Definition 5.2. We define the daily *Charging Station Occupation Rate (CSOR)* of a station s_j to quantify the average occupation time of each charging point in the station, which is formulated as:

$$CSOR(s_j) = \frac{\sum_{i=1}^{n_j} T_s(e_{ij})}{p_j} \tag{9}$$

Where $T_s(e_{ij})$ is the *service time* of ith charging event e_i in the station s_j; n_j is the daily number of charging events in the station s_j; p_j is the number of charging points in station s_j. To balance the charging station utilization, we need to reduce the number of charging stations with very low or very high CSORs since a very low *CSOR* means a charging resource waste and a very high *CSOR* means potential longer *queuing time* in those charging stations.

5.3 Recommendation Results

5.3.1 Comparison of Traveling Time. As shown in Figure 13, the *OCSD* has smaller PRTT than *Recommender*, but FairCharge achieves higher *traveling time* reduction than *OCSD*. The reason why *OCSD* achieves better performance of PRTT than *Recommender* may be that *Recommender* will recommend the stations with more *queuing time* reduction and sacrifice the *traveling time*. The figure shows that the least PRTT is around 4:00 in the morning and the *traveling time* is long in the early morning. The reason may be that the charging demand in the urban area is too high during these non-rush hours, so ETs need to go to suburban areas to charge for reducing the *queuing time*. The distance from urban business areas to suburban is very far, resulting in the *traveling time* is long. Another change shift time is around 17:00, so the *traveling time* to stations is also longer in this duration.

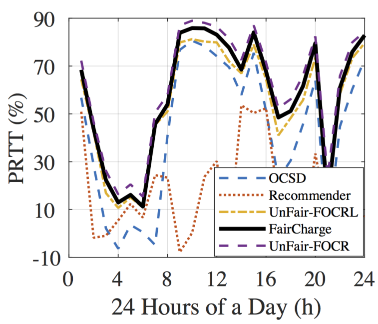

Fig. 13. Traveling time reduction.

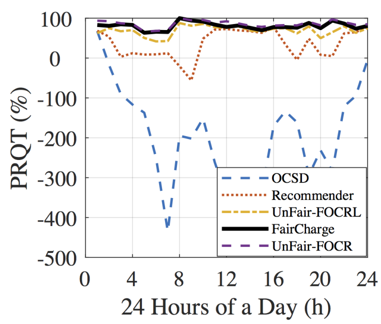

Fig. 14. Queuing time reduction.

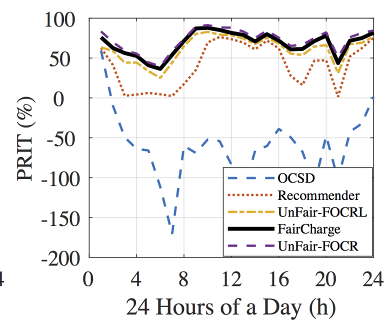

Fig. 15. Idle time reduction.

Even though we found that *UnFair-FOCR* has the best immediate performance if we do not consider fairness, which is slightly better than our FairCharge, we found about 11% recommendations in *UnFair-FOCR* are not fair, which potentially makes these ET drivers not to follow recommendations from *UnFair-FOCR*, so the performance of *UnFair-FOCRL* is worse than our FairCharge after considering fairness on the long-term perform.

Table 2 shows the average PRTT for each charging event. Combining the immediate performance and the potential following rates, we found that our FairCharge has better long-term performance, which reduces the *traveling time* by 58.7% compared to the Ground Truth, decreasing from 11.3 minutes to 4.65 minutes. However, some drivers will not follow *UnFair-FOCR* because of unfair recommendations, which causes a 55% deduction of *UnFair-FOCRL* compared to the Ground Truth. *Recommender* and *OCSD* also reduces *traveling time* by 16.7% and 47.7%, respectively.

Table 2. Average percentage reduction of traveling time.

Methods	OCSD	Recommender	UnFair-FOCRL	FairCharge	UnFair-FOCR
PRTT	47.7%	16.7%	55%	58.7%	61.8%

5.3.2 Comparison of Queuing Time. Figure 14 shows the PRQT of different recommendation methods. We found that *OCSD* has the worst performance regarding PRQT, and it will have negative PRQT during most hours, which means that the average *queuing time* of *OCSD* is longer than the Ground Truth. The reason is that there will be heavy charging peaks under *OCSD* since too many ETs operating in urban business areas will be recommended to the same charging stations by *OCSD*, leading to an increase of the *queuing time*. Especially during some charging peak hours in one day, e.g., 5:00-6:00, 12:00-13:00, *OCSD* causes extremely long *queuing time*, so it might not be a good recommendation for ET fleets. However, our FairCharge achieves more than 80% of PRQT on average, and it is also better than *Recommender* and *UnFair-FOCRL*.

Table 3 shows the average PRQT for each charging event, and we found that our FairCharge reduces the *queuing time* by 80.2% compared to the Ground Truth, decreasing from 8.01 minutes to 1.59 minutes. While for *UnFair-FOCR*, with the potential user loss, the performance of *UnFair-FOCRL* is about 7% worse than our FairCharge from a long-term perspective.

Table 3. Average percentage reduction of queuing time.

Methods	OCSD	Recommender	UnFair-FOCRL	FairCharge	UnFair-FOCR
PRQT	-193.1%	35.8%	73.1%	80.2%	82.1%

5.3.3 Comparison of Idle Time. As shown in Figure 15, with fairness consideration, we found that our FairCharge achieves the largest PRIT. More specifically, FairCharge achieves over 50% PRIT for charging requests almost in all hours of a day. *Recommender* also achieves a good performance in terms of the PRIT, but it is not as good as FairCharge. Compared to the Ground Truth, *OCSD* shows a worse performance on PRIT because of its prolonged *queuing time*.

Table 4 shows the average PRIT for each charging event, and we found that our FairCharge reduces the *idle time* by 67.7%, i.e., decreasing from 19.31 minutes to 6.24 minutes, which is about 5% better than the optimal unfair batch-based recommendation *UnFair-FOCRL* considering the long-term performance.

Table 4. Average percentage reduction of idle time.

Methods	OCSD	Recommender	UnFair-FOCRL	FairCharge	UnFair-FOCR
PRIT	-61.0%	41.3%	62.5%	67.7%	70.2%

To show the individual performance under different methods, we show the idle time distribution of each charging event in the box-plot Figure 16. We found that under our fairness-aware FairCharge, the maximum idle times of all charging events have significantly decreased, i.e., from 160 minutes to 24 minutes, while some drivers need to spend 55 minutes under the optimal unfair batch-based recommendation UnFair-FOCR, which will potentially cause these drivers do not follow their recommendations later. With our fairness consideration, the recommendations will become more acceptable for all ET drivers, which means that the maximum prolonged time for all drivers is minimized compared to their utopia decisions, i.e., the worst case for each driver is not too bad. Hence, compared to other state-of-the-art charging recommendation, our FairCharge achieves the best performance, considering the long-term idle time reduction.

Potential Benefits. In summary, we found that our FairCharge achieves the highest *idle time* reduction in the long-run with the fairness consideration. Specifically, the average *idle time* of our FairCharge is about 6.24 minutes for each charging event, while the Ground Truth is 19.31 minutes and *Recommender* is 11.33 minutes. Compared with *Recommender*, especially for the Ground Truth, FairCharge saves over 13 minutes for each charging event.

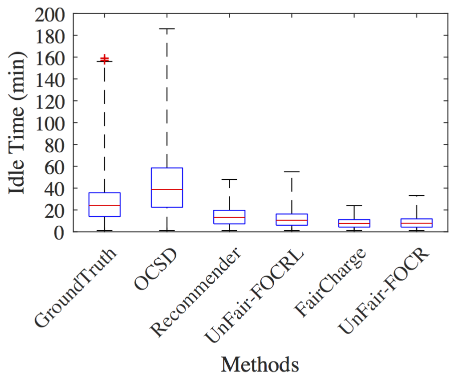

Fig. 16. Idle time distribution comparison of different recommendations.

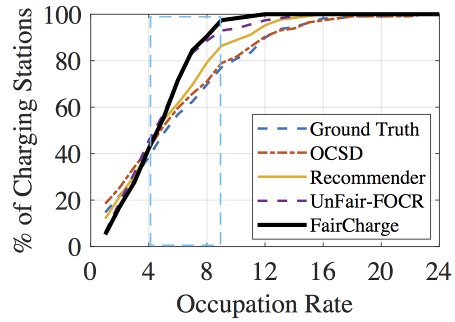

Fig. 17. Charging station occupation rate comparison.

In fact, even one-minute saving for each charging event (i.e., 5% of improvement) can be significant, given a large number of ETs and their frequent charging activities. In particular, each ET usually charges about three times a day. Hence, our FairCharge potentially reduces about 627,360 minutes idle time compared with the optimal individual recommendation *Recommender* for the ET fleet per day. These 627,360 minutes can help the ET fleet to potentially pick up more than 35,855 passengers (if additional demand was given) in one day, which can potentially improve passengers' traveling satisfaction (e.g., reducing passengers' waiting time) and enhance the mobility of the city.

5.3.4 Charging Station Occupation Rate (CSOR). Figure 17 shows the *CSOR* of different recommendation methods. We found that the *CSOR* under FairCharge can be more balanced, e.g., more charging stations have medium occupation rates from 4 to 9, and fewer charging stations have very high or very low occupation rates. The percentage of charging stations with *CSOR* between 4 and 9 has increased from 46.8% to 69.8% by the FairCharge recommendation, which indicates our recommendation has the potential to balance the uneven spatial charging demand phenomenon. Our FairCharge also achieves a better charging station utilization than *UnFair-FOCR*, which potentially makes our recommendation also fair to charging station utilization.

5.3.5 Impact of Driver Participation Rate. For this project, we are working with the Shenzhen Transportation Committee to design a centralized charging recommendation system for effective charging management. Shenzhen Transportation Committee monitors the operating status of all ETs in Shenzhen and provides data access for us. When replacing conventional gas taxis into ETs, the Shenzhen government provides a large number of subsidies for taxi operators to incentivize taxi drivers to adopt ETs and follow its initiatives, so we envision that ET drivers will follow our charging recommendation decisions to obtain their subsidies and social benefits. However, even in this case, some drivers may still not follow our recommendation strategy. Hence, we further investigate the system performance when some ET drivers do not follow our recommendation decisions and show how they may affect the system as a whole.

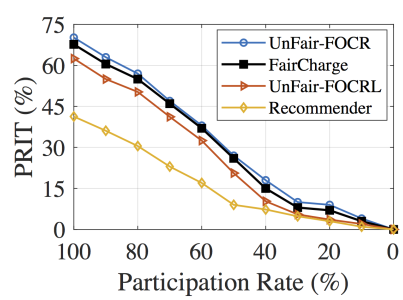

Fig. 18. Performance under different participation rates.

As shown in Figure 18, we compare our FairCharge with the three methods of best performance regarding the idle time reduction. Even though *UnFair-FOCR* has slightly better performance than FairCharge under the same participation rate, but it should be noted that more drivers will not follow *UnFair-FOCR* due to its unfair recommendations. Hence, combined with the ideal performance and fairness consideration, our FairCharge has better performance than its long-term performance *UnFair-FOCRL*. We also found that the system performances of all recommendation systems decrease with fewer drivers participating in the recommendation, but our FairCharge achieves a better performance than *Recommender*. Especially when the participation rate drops to below 50%, the PRTT of all systems decreases a lot.

6 DISCUSSIONS

In this section, we first report some lessons learned about the fairness-aware recommendation and real-world insights from field studies. Then we discuss some possible factors that will impact our system, followed by some potential implications, e.g., implementation in different cities and the data release.

6.1 Lessons Learned

- **Fairness-Aware Charging Recommendation.** Although there is no unique definition of fairness, it is undeniable that fairness plays a critical role in the recommendation systems [50]. In this paper, we take the "least misery" [39] definition of fairness as our design guideline after exploring many existing fairness related works [1, 12, 39, 50, 51], which we believe best matches the driver incentives, to show how this fairness consideration effectively helps real-time charging recommendation.
  Even though the optimal unfair recommendation *UnFair-FOCR* can achieve better short-term performance than our FairCharge, we found that about 11% of the charging events under *UnFair-FOCR* recommendation are not fair for some drivers, which may result in these drivers not following the recommendations from *UnFair-FOCR*, so our FairCharge can achieve better performance than unfair *UnFair-FOCR* in the long run (i.e., *UnFair-FOCRL*). Hence, we argue that fairness is an important consideration that guides us to design better recommendation systems [1].
- **Real-World Insights.** During our project, we have been conducting a series of field studies in Shenzhen, and we talked to 12 ET drivers. Even though some drivers mention there is an increasing number of charging stations and charging points in the city, the queuing phenomenon in some charging stations during some durations is still serious. The possible reason is that lacking coordination among ET drivers, so they will go to the same charging stations that they are familiar or these locations are convenient for them to rest. Some drivers said they hope there will be a good App that guides them to the best choices. Although there are some existing Apps provide charging recommendation for them, ET drivers find them ineffective due to limited coverage of charging stations (e.g., only provides charging station information of a specific operator) and biased recommendation, so they think our work could be valuable if we include all ET charging stations and make fair recommendations. They also mention it would be better if there are some spaces for them to have some rest. We report all insights from our project to the city government, and all of them are well received and under implementation.

6.2 Possible Impact Factors

Participation and Incentives. Our system is under the assumption that all ETs in this fleet will follow our recommendation. Still, it is possible that some drivers may not follow the recommendation despite the fact that they know the recommended decisions can reduce idle time for them. Even though our fairness consideration can potentially offer an incentive for drivers to accept our recommendation, we can still design some incentive mechanisms like "virtual electricity" [52] to further encourage participation in real-world operation.

Time for Serving Passengers. Even though we do not explicitly consider the time for serving passengers in our modeling, it is implicitly included in our system since we make recommendation decisions for drivers after they send charging requests. Based on our data-driven observations in Section 3.2, drivers usually charge during non-rush hours (e.g., 0:00-6:00), which is formed after operating ETs for several years. We believe reducing their charging time can potentially increase their operating time and increase their profits. As a result, our optimization objective is minimizing the charging time instead of the time for seeking passengers, which is usually the objective of conventional gas taxis [8, 27, 45].

Income-Fairness of Drivers. Income-fairness could be more important for drivers than waiting-time fairness. In this paper, to make our design more practical, we also consider some real-world factors (e.g., drivers' charging intentions) for charging recommendations. For our FairCharge recommendation system, it only makes recommendation decisions for drivers after they send charging requests, which means our FairCharge implicitly considers drivers' charging intentions, so we will not recommend them to charge during rush hours if they do not send charging requests in these periods, which potentially reduces their income loss. In future work, we will further consider the income-fairness of drivers to enhance our system, e.g., proactively sending recommendation suggestions to drivers during the non-rush hours and balance their income.

Remaining Battery Level Constraint: As we mentioned in the Introduction part, to make our design more practical, we only recommend ET drivers to the corresponding charging stations when they send charging requests instead of deciding when they need to go to charge. In real-world scenarios, due to the "range anxiety" of ET drivers, they will typically go to charging stations to charge their ETs when the battery capacity decreases to about 20%, which is enough for traveling more than 50 km. As shown in Figure 4, the distance between two charging stations is typically shorter than 3km, and the size of Shenzhen is about 50km * 25km, so ETs can always reach a charging station when they send charging requests. In addition, since we add a "least misery" constraint to guarantee the fairness between different ET drivers, so recommendation decisions for all ET drivers are not too bad for them, and our solution always guarantees that all ETs can reach a charging station from their current locations. Hence, the remaining battery level would not impact our system.

Impact of Private EVs. Even though some charging stations may be shared by private vehicles with taxis, few private EVs in Shenzhen prefer to utilize fast charging stations of ETs for the following reason: Private EVs used for daily commuting have no needs to leverage fast charging like commercial EVs, which rely on 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. We also verify this during the field studies in Shenzhen, as Figure 12 indicates. Based on this, we envision that other EVs have little impact on the ET recommendation, which is also adopted by some other related research [16, 30, 32, 35].

Possible Charging Requests. In this work, we design a batch-based recommendation, which means some drivers may need to wait one minute for a recommendation. In the future, we can still improve this in some other ways. (i) Integrating a charging reservation mechanism in our recommendation system, which means ET drivers can send their charging requests to us in advance to avoid waiting. (ii) Predicting the charging requests. Due to the time sequence nature of our GPS data and the relatively stable charging time of each driver, it is easier for us to leverage some advanced deep learning algorithms, e.g., Long Short Term Memory networks (LSTMs) [7, 11] to predict the charging requests in a near-future duration. Even though considering charging requests in a longer future may bring about better performance, it also requires more computational resources, which are currently not possessed by our local partners in Shenzhen. Since our key contribution of this paper is fairness-aware charging recommendation instead of charging request prediction, we do not emphasize detailed prediction issues.

6.3 Potential Implications

Generalization. Although we only study the fairness-aware charging recommendation problem of ETs in this paper, we believe our system is also applicable for other types of electric vehicles (e.g., electric for-hire vehicles, electric private vehicles, etc) since we make recommendation decisions based on their requests and fairness considerations. In the next step, we are trying to utilize data from electric for-hire vehicles to verify our system. In addition, our fairness-aware model also has the potential to be generalized to other research, e.g., fairness-aware for-hire vehicle order dispatching.

Implementation in Different Cities: In this paper, even though we only leverage the data from the Chinese city Shenzhen to verify our FairCharge, we are in the process of obtaining ET data from other cities to investigate if our recommendation system is applicable to other cities. However, since only Shenzhen has such a large-scale ET fleet, it is challenging to find other large-scale ET fleet for a parallel study currently. One possible direction we are exploring is to design transfer learning models to transfer the knowledge (e.g., operating pattern, charging pattern) from the Shenzhen ET network to other cities for a "what if" investigation. For example, what if all conventional gas taxis in New York City or Beijing were replaced by ETs, how many charging stations are enough by adopting our fairness-aware charging recommendation. It opens some very interesting research directions.

Data Management and Privacy Protections. In this project, we establish a secure and reliable transmission mechanism with a wired connection, which feeds our servers the filtered ET data wirelessly collected by Shenzhen transportation committee via a cellular network. For daily management and processing, we utilize the MapReduce based Pig and Hive, which is built on a cluster with 34 TB Hadoop Distributed File System (HDFS). The cluster consists of 11 nodes, each of which is equipped with 32 cores and a 32 GB RAM. Since our recommendation system needs detailed driver location and behavior data, our collaborators in Shenzhen has a contract with ET drivers, and the drivers consent that their data while working as ET drivers can be used by the company to improve the system performance. Also, since our system considers fairness for drivers, we expect no protest from them. Nevertheless, we carefully replace each ID with a unique serial number.

Data Uniqueness. ETs have essential differences from conventional gas taxis due to their long charging time, so most existing works related to gas taxis are not suitable for ET research given distinct charging time and refueling time. Even though many cities worldwide have initiatives for promoting ETs, the ET scales are still limited. Fortunately, as a pioneer of promoting ETs, ETs in Shenzhen have experienced encouraging growth during the last few years, and the number of ETs has reached a scale of 16,000. Our dataset from Shenzhen Transportation Committee, to our knowledge, has the potential to provide valuable insights for future ET fleets.

7 RELATED WORK

As a key challenge to promote ETs, the charging issue is the focus of the academic community on ET studies. In this section, we organize the electric vehicle (EV) charging related work into three categories, i.e., (i) charging station planning and deployment, (ii) charging load balancing on the power grid, and (iii) charging recommendation.

7.1 Charging Station Deployment

Most existing EV research is focused on charging station deployment [4, 16, 18, 28, 42, 43], and their objective is to find the optimal locations to deploy charging stations and optimally assign charging points to each station. With the rapid promotion of EVs, deploying more new charging stations becomes the most direct approach to facilitate the charging of EVs for reducing their queuing time, so there are lots of EV-related research in this direction. Li et al. [16] developed a charging station deployment and charging point placement framework to minimize the charging time. They mentioned the potential recommendation method, but they did not consider the charging station utilization rates and fairness between drivers, which may cause a more unbalanced charging resource utilization and low driver penetration. Even though charging station deployment sometimes has the same objective as our charging recommendation, i.e., reducing the overall charging overhead for longer operation time, the approaches are different. i.e., adding new resources vs. utilizing existing resources. In addition, more charging stations mean more costs, e.g., a fast charging station with only 10 charging points costs over $358,000, not considering the cost of the land resources [29]. Moreover, for large cities like New York City, Hong Kong, and

Beijing, the land resources are scarce and hardly available for large charging stations. Further, enough charging stations cannot guarantee there is an available charging point in a specific station for an ET, e.g., too many ETs going to the same station (i.e., spatial clustering) will lead to the long queuing phenomena in this station, the same with the temporal clustering, which means most ETs go to charge in the same time. Hence, our recommendation is more efficient in practical applications.

7.2 Charging Load Balancing

Charging load balancing is also an important direction of EV research [13, 14, 21], which analyzes the energy consumption of EVs and the impacts of charging behaviors on the grid. Although it also considers the charging time, the objective of charging load balancing is to reduce the influence of charging on the smart grid, which is different from our work. Kong et al. [13] designed an effective charging rate control algorithm to maximize the social welfare of EVs. However, each ET has its own charging pattern and duration, and they have influences on each other, e.g., an ET needs to charge longer if the battery level is low, which leads to a nondeterministic charging activity.

7.3 Charging Station Recommendation

Charging recommendation [23, 30, 35, 36, 38, 44] aims to recommend each EV to a charging station for some benefits, e.g., shortest time spent, lowest money cost based on existing charging infrastructure, but almost all of the existing research focuses on the individual recommendation. Tian et al. [30] designed a charging recommendation model considering only one request from an individual ET, but they do not consider potential charging requests, which will cause a suboptimal recommendation. The individual-based recommendation is based on greedy algorithms, which may provide a single step optimal charging station recommendation for each request, but 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. Park et al. Park et al. [23] developed a reservation recommendation algorithm for EVs, which considered the shortest distance to charging stations, and then recommended the vehicles to the stations with the shortest queuing time, while possible traffic congestion and potential requests from other EVs have not been considered. More importantly, all these works did not consider the potential unfair charging station allocations.

Technically, the key advantage of our method is that we fully leverage the rich fleet information combined with a suitable fairness definition to achieve a fairness-aware Pareto efficient recommendation, which makes our work very different from existing works. Moreover, we minimize the idle time for charging without building extra charging infrastructures. Hence, our Pareto efficient fairness-aware recommendation is more economically effective compared to existing methods.

8 CONCLUSION

In this paper, we design the first fairness-aware charging recommendation system called FairCharge based on multi-source data, which aims to achieve the Pareto efficient fairness-aware charging recommendation for the entire ET fleet in a city. We formulate the charging recommendation problem as fairness constrained Pareto optimization. To feed the recommendation system, a context-aware traveling time model at the road segment level is designed based on the distances and the traffic conditions, which is then leveraged to infer the traveling time, and a fleet-oriented queuing time calculation model is developed by considering the status of all relevant ETs in the fleet. We then leverage the scalarization with greedy algorithm, coupled with Pareto improvement to find the optimal fair solution. Finally, we implement and extensively evaluate FairCharge with real-world ET data from the Chinese city Shenzhen, including GPS records and transaction data of more than 16,000 ETs, combined with data of 117 charging stations. The evaluation results show that our FairCharge reduces 80.2% of the queuing time and 67.7% of the idle time, simultaneously.

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