sharedCharging: Data-Driven Shared Charging for Large-Scale Heterogeneous Electric Vehicle Fleets

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Our society is witnessing a rapid vehicle electrification process. Even though being environmental-friendly, electric vehicles have not reached their full potentials due to prolonged charging time. Moreover, unbalanced spatiotemporal charging demand/supply along with the uneven number of charging stations between heterogeneous fleets make electric vehicle management more challenging, e.g., surplus charging stations across a city for electric buses but limited charging stations in some regions for electric taxis, which severely limit the charging performance of the whole electric vehicle network in a city. In this paper, we first analyze a large-scale real-world dataset from two heterogeneous electric vehicle fleets in the Chinese city Shenzhen. We investigate their mobility and charging patterns and then verify the practicability and necessity of shared charging. Based on the insights we found, we design a generic real-time shared charging scheduling system called sharedCharging to improve overall charging efficiency for heterogeneous electric vehicle fleets. Our sharedCharging also considers sophisticated real-world constraints, e.g., station spaces, availability of charging points, real-time timetable guarantee, etc. More importantly, we take the electric bus and electric taxi fleets as a concrete example of heterogeneous electric vehicle fleets given their different operating patterns. We implement and evaluate sharedCharging with streaming data from over 13,000 electric taxis and 16,000 electric buses, coupled with the charging station data in the Chinese city Shenzhen, which is the largest public electric vehicle network in the world. The evaluation results demonstrate that the proposed sharedCharging reduces the waiting time by 63.5% and reduces the total charging time by 15% on average for e-taxis.

CCS Concepts: • **Networks → Mobile networks**; *Cyber-physical networks.*

Additional Key Words and Phrases: Data-driven; charging scheduling; electric vehicle; electric taxi; electric bus

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1 INTRODUCTION

Vehicle electrification has been a worldwide popular trend because of the environmental-friendly nature of electric vehicles (EVs) and ever-increasing concerns over the security of energy supply [43]. There are over 385,000 electric buses (e-bus) in 2017 globally, and it is predicted that the figure will increase to 1.2 million by 2025, which is nearly the half of the worldwide city bus fleet [12]. New York City has the initiative to replace one-third of its taxis with EVs by the end of 2020 [9]. In addition, it is expected more than 9,000 electric taxis (e-taxi), roughly 50% of the current taxi fleet in London, will run on London's roads by 2021 [32]. Moreover, there is an increasing number of countries deciding to ban fossil fuel vehicles and expecting all EVs in their countries [46], which indicates that EVs have a promising future [1].

Although the obvious advantages of mitigating air pollution, the unique characteristic of commercial EVs, i.e., long daily operating time compared to private vehicles, results in higher energy consumption and more frequent charging activities, which make it essential to deploy a large number of charging points to satisfy their daily operations [42]. However, some real-world factors, e.g., expensive costs of charging infrastructures, make it challenging to deploy abundant charging points to avoid long queuing phenomena in charging stations at the early promotion stage. For example, the average cost for building a charging station with only 10 charging points will be over 735,000 US dollars [17]. In addition, land resources for charging stations are extremely scarce in some large cities, e.g., New York City, Beijing, and Shenzhen. Hence, high infrastructure costs and the limited land resources make it difficult to have abundant charging stations and charging points for all EVs. Finally, even though there is theoretically enough charging infrastructure for all EVs, the uncontrolled and decentralized charging behaviors of some EV fleets, e.g., e-taxi fleets, cause the long queuing phenomena for available charging points when they intensively charge during some specific time durations [43].

Much existing research [7, 24, 25, 27, 50] focuses on how to choose the optimal locations for charging stations and how to assign charging points in each station to minimize the charging time of EVs considering some passenger demands or cost constraints. However, to our knowledge, almost all these works [7, 25, 28, 41, 44, 50–52] only consider one fleet (e.g., only e-taxis [7, 25] or e-buses [44]). Different mobility patterns and charging patterns of heterogeneous EV fleets have not been considered based on real-world data. Moreover, only considering a single fleet may achieve a local optimum but the global optimum can hardly be obtained since some other fleets' charging infrastructures may potentially be used to improve the charging efficiency of the whole charging network. In this paper, we argue that shared charging has the potential to solve this local optimum problem and enhance the overall charging efficiency for all fleets in urban transport networks through resource sharing. However, shared charging among heterogeneous EV fleets is also extremely challenging caused by their different operating patterns.

- Heterogeneous EV fleets (e.g., e-taxis and e-buses) with different purposes have various operating patterns, which leads to **different mobility patterns**. For example, buses are large and have fixed routes with timetable constraints to satisfy the passenger demand; whereas taxis are small and have flexible operating time since they cruise around the city to meet the stochastic travel demand. These different operating patterns lead to various **real-world constraints**, which makes the shared charging scheduling challenging.
- Different charging policies for heterogeneous EV fleets because of their purposes result in unbalanced spatial distributions of charging resources and **different charging patterns**. For example, transit buses are operated for satisfying peoples' daily life, so e-bus operators can obtain enough land resources to deploy charging points across a city for satisfying buses' daily operation, while e-taxi charging stations are mostly in some areas due to their business characteristics. In addition, e-buses are under centralized management of bus operators, and their charging schedules are controllable. Based on real-world observations and our data analyses, e-bus companies tend to charge their e-buses at midnight to reduce their operating costs due to the time-varying electricity pricing mechanism (i.e., low electricity price in off-peak night

hours) [44], which results in many charging points in e-bus charging stations are unoccupied during the daytime. While we found e-taxis always have several intensively charging peaks in the daytime due to their two-shift operating pattern and limited battery capacity, which causes prolonged waiting time in charging stations. These observations are shown in our data-driven investigation in Section 3. Hence, the unbalanced deployment of charging stations and different charging patterns make the shared charging more challenging.

Combining the above two factors, it is challenging to schedule large-scale heterogeneous EV fleets for shared charging under a real-world data-driven setting. To solve these challenges, in this paper, we design sharedCharging, a real-time shared charging scheduling system for heterogeneous EV fleets, which schedules different sizes of EVs with different operating patterns (e.g., e-taxis and e-buses) to improve the overall charging efficiency of the charging network in a city. In particular, the key contributions of this paper include:

- To the best of our knowledge, this is the first data-driven framework to coordinate the charging events of large-scale heterogeneous EV fleets with different operating patterns and social purposes, which aims to improve the overall charging efficiency (e.g., reducing the charging overhead, balancing the uneven charging resource allocation and utilization) by sharing charging resources. We conduct a comprehensive comparative study on mobility and charging patterns of two heterogeneous EV fleets, including over 13,000 e-taxis and 16,000 e-buses in the Chinese city Shenzhen, to identify their real-world features and the potential benefits of shared charging, which have not been studied before.
- Based on the insights obtained from our data-driven comparative analyses, we design a shared charging scheduling system called sharedCharging, where we formulate a heterogeneous EV fleet scheduling problem into a classical scheduling problem (i.e., two-type heterogeneous multiprocessor real-time scheduling). Moreover, sharedCharging considers a few real-world constraints, e.g., station spaces, availability of charging points, real-time timetable guarantee, and drivers' participation rates when making scheduling decisions, which make our sharedCharging more practical for real-world implementation.
- More importantly, we implement and extensively evaluate our sharedCharging based on a real-world dataset from two heterogeneous EV fleets in the Chinese city Shenzhen. The evaluation results indicate that our shared charging scheduling reduces the charging waiting time by 63.5% and the total charging overhead by 15% on average for each charge of e-taxis, while keeping timetables of the e-bus fleet at the same time. Moreover, sharedCharging effectively improves an unbalanced charging station utilization problem for both of the two EV fleets.
- Finally, we provide some in-depth discussions for the insights and lessons learned from our data-driven investigation and scheduling, which can potentially provide policy guidelines and experiences for other cities that plan to promote large-scale heterogeneous EV fleets and shared autonomous EVs in the future.

The rest of the paper is organized as follows. Section 2 introduces our dataset. Section 3 presents a detailed data-driven investigation. Section 4 describes the design and implementation of sharedCharging. Section 5 evaluates the performance of sharedCharging. Some lessons learned and limitations are summarized in Section 6. In Section 7, we discuss the related work, followed by the conclusion of this paper in Section 8.

2 DATA DESCRIPTION

By collaborating with Shenzhen Transportation Committee, we are fortunate to have access to an extremely large real-world EV dataset collected from the Chinese city Shenzhen. Shenzhen has 12 million population, and its size is about 792 mi^2. Our datasets include data from two large-scale heterogeneous EV fleets, i.e., a 16,000 e-bus fleet and a 13,000 e-taxi fleet. One of the most popular e-bus models in Shenzhen is BYD K9 [8]; whereas all e-taxis in Shenzhen are BYD E6 [2]. The specifications of the two EV models are in Table 1.

Table 1. Specifications of one type e-taxi model and e-bus model in Shenzhen.

Model	Battery Capacity	Charging Rate	Maximum Distance	Maximum Speed
BYD E6	57 kWh	30 kW	300 km	140 km/h
BYD K9	324 kWh	100 kW	250 km	90 km/h

Table 2. An example of all datasets.

Bus GPS	plateID	lineID	longitude	latitude	time
	BSXXXXD	M4893	114.022901	22.532104	2018-01-14 00:00:04
Taxi GPS	plateID	longitude	latitude	time	speed(km/h)
	SZDXXXX	114.022901	22.532104	2016-06-16 08:34:43	22
Charging Station	stationID	stationName	longitude	latitude	number of charging points
	30	NB0005	113.9878608	22.55955418	40
Road Network	roadID	startLongitude	startLatitude	endLongitude	endLatitude
	27813	114.426971	22.604326	114.4370363	22.5904528

There are four different types of data sources used in this paper, i.e., the bus GPS data, the taxi GPS data, the charging station data, and the road network data. An example including some primary fields of each of the four datasets is shown in Table 2, followed by their details.

- **Taxi GPS Data** include over 80 billion taxi trajectory points with a size of over 15 TB from June 2013 to September 2018, coupled with transaction data of passengers. Each GPS record consists of 13 fields that describe stationary attributes and dynamic information of a taxi, e.g., the vehicle ID, the longitude & latitude, time-stamp, speed, and the occupied flag. The GPS data are collected by an onboard device in each taxi with a cellular connection.
- **Bus GPS Data** include over 8 TB data from the same duration with taxi GPS data. Each bus GPS record comprises 19 fields that describe vehicle ID, line ID, position (i.e., the longitude and latitude), time-stamp, current direction, current speed, odometer reading, etc.
- **Charging Station Data** include the ID and name of each e-bus and e-taxi charging station, the station location (i.e., longitude and latitude), the number of charging points in each charging station, and the opening date for these stations.
- **Road Network Data** include all 135 thousand road segments and 87 thousand road intersections in Shenzhen. Each road segment has a road ID, road name, its length, road types, etc.

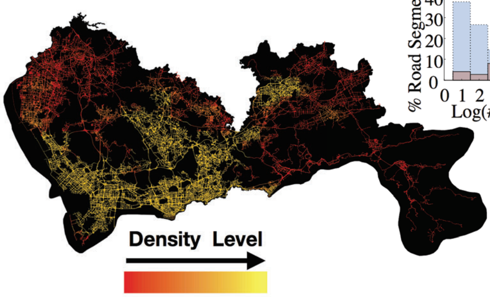
Based on these datasets, we utilize different approaches to extract charging events in charging stations of e-taxis and e-buses from their GPS data. For e-taxis, their GPS modules will still upload records to our servers when they are charging, so we utilize a widely used spatiotemporal constraint-based method from existing works [25, 41] to extract their charging events. For the temporal constraint, we extract the potential charging events from e-taxis' trajectory data based on the fact that an e-taxi will stay for a long time (e.g., 30 minutes) at the same location to have a charge, which is represented by a sequence of GPS data points in the same position. Next, we consider the charging station location data, i.e., the spatial constraint to obtain true charging events, which means the charging events must happen in charging stations (e.g., ranges of using charging station locations as centers and 200 meters as radii [41]). We also conducted a set of field studies to filter some noise and verify the algorithm performance at different charging stations in Shenzhen on June 20th, 2017 and May 26th, 2018. The results show that this method can yield an accuracy of 96%. For e-buses, their GPS modules will stop uploading records when they are charging, so we can easily extract their charging events from their GPS data, which means that the interval between two adjacent GPS records larger than a threshold (e.g., 30 minutes) is extracted as a charging event of an e-bus.

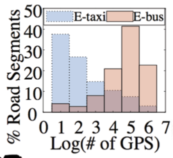
3 DATA-DRIVEN INVESTIGATION

In this section, we conduct a comprehensive comparative investigation on mobility and charging patterns of two heterogeneous EV fleets based on the real-world data described in Section 2, from which we show the practicability and opportunity for shared charging.

3.1 Mobility Patterns of Heterogeneous EV Fleets

Figure 1 and Figure 2 show mobility visualizations of Shenzhen e-taxi and e-bus fleets on road segment levels. The yellow parts stand for more EV activities, e.g., more GPS records at those locations, and the red parts mean fewer vehicle activities. We found that the e-bus fleet has larger high-density coverage than the e-taxi fleet in Shenzhen. The reason is that all buses in Shenzhen are e-buses and they travel across the city to serve passengers, so most road segments with bus lines have higher GPS density. However, different from traditional gas taxis, e-taxi drivers prefer to cruise near charging stations due to their “range anxiety” [41] or places with higher passengers' travel demand, which results in more concentrated activities of e-taxis in these areas. The figure between Figure 1 and Figure 2 shows the number of e-taxi and e-bus GPS records on road segments. We found that over 85% of road segments have more than 10^4 e-bus GPS records per day; whereas the percentage is about 20% for the e-taxi fleet. These phenomena indicate e-taxis have a concentrated and limited activity range, which may cause some charging stations overcrowded and long waiting time for available charging points.





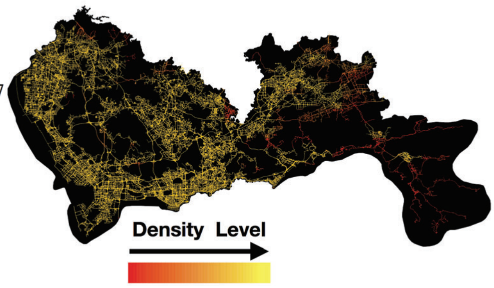


Fig. 1. E-taxi activities in Shenzhen.

Fig. 2. E-bus activities in Shenzhen.

From Figure 3, we found that the daily operating distance of 92% of e-buses is shorter than 250 km; whereas the daily operating distance of only 2% of e-taxis is shorter than 250 km. Figure 4 shows the Cumulative Distribution Function (CDF) of operating distances of e-buses and e-taxis between two continuous charges (i.e., per-charge distance). We found that e-buses and e-taxis have similar patterns. Moreover, about 80% of e-buses and e-taxis will charge before operating over 185 km, although e-buses travel a slightly longer distance than e-taxis after charging due to their larger battery capacity. Considering both the daily operating distance and per-charge distance, we found that e-taxis potentially have a higher charging frequency than e-buses, results in more daily charging events of e-taxis.

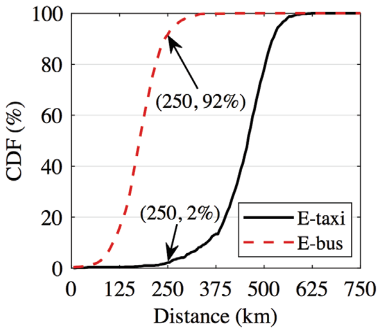


Fig. 3. Daily operating distance.

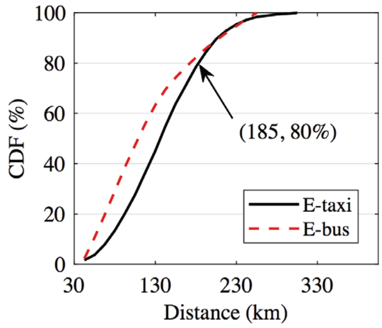


Fig. 4. Operating distance after a charge.

3.2 Charging Patterns of Heterogeneous EV Fleets

Under Charging Time: Figure 5 and Figure 6 show the cumulative daily under charging time (i.e., with chargers plugged in) and per-charge time of e-taxis and e-buses. We found that e-buses tend to have longer under charging time than e-taxis, e.g., about 88% of charging events of e-taxis are shorter than 2 hours but only 58% of charging events of e-buses are shorter than 2 hours because of their different battery capacities, and there is a similar pattern for the daily under charging time as shown in Figure 5, which implicitly indicate that e-taxis may prefer shorter under charging time to save time for operating. The typical number of charges in a day for e-taxis and e-buses are 2-4 and 1-2, respectively.

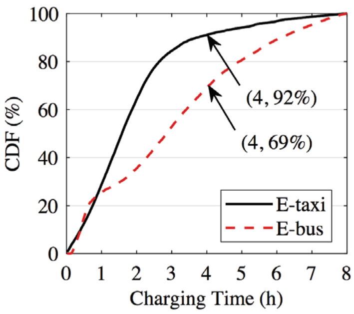


Fig. 5. Cumulative daily under charging time.

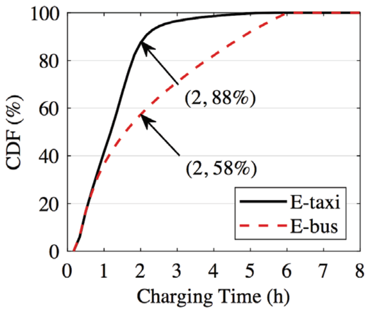


Fig. 6. Time for a charge.

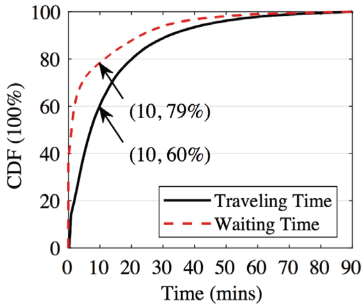


Fig. 7. CDF of time to stations and waiting time in stations of e-taxis.

Traveling Time & Waiting Time of E-taxis: We then study the time an e-taxi spend for going to charging stations (i.e., traveling time) and the time for waiting for available charging points in stations (i.e., waiting time). Figure 7 shows the CDF of the traveling time to charging stations and the waiting time in stations of e-taxis. Although 60% of the charging activities' traveling time is shorter than 10 minutes, there are still 20% of charging activities where drivers need to travel over 20 minutes to charging stations. Some drivers even need to spend more than an hour to go to a charging station. For the waiting time, we found that 80% of charging activities has waiting time shorter than 10 minutes, but there are still 15% of charging activities costing more than 20 minutes for waiting. Hence, one intuitive idea is that if e-taxis can utilize e-bus charging stations, their traveling and waiting time can potentially reduce, which is validated in Section 5.

Figure 8 shows the average traveling time and waiting time of the e-taxi fleet spent for charging. We found that the waiting time has a similar pattern with the charging event distribution of e-taxis in Figure 9, e.g., longer waiting time happens at 0:00-4:00 and 16:00-18:00, which are the charging peaks of the e-taxi fleet. Since the

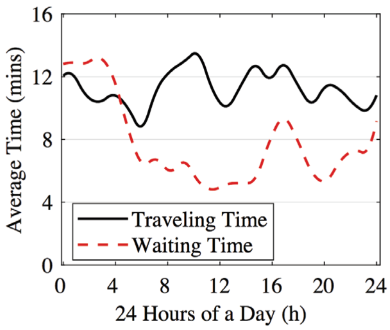


Fig. 8. Average time to stations and waiting time in stations of e-taxis.

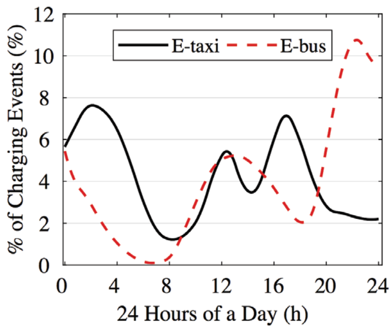


Fig. 9. Charging events distributions of e-taxi and e-bus fleets.

charges of e-buses are centrally managed by the operators, the traveling time of e-buses is controllable given that their scheduling decisions are always made when they arrive at terminals. The waiting time is also is controllable since bus operators have charging scheduling plans for their fleets to guarantee the daily operation, which is different from e-taxis charging where e-taxi drivers make charging decisions by themselves. Hence, the waiting time of e-buses is also controllable, so we do not show the traveling time and waiting time of e-buses here.

3.3 Opportunities for Shared Charging

The obvious differences of mobility and charging patterns between the e-bus fleet and e-taxi fleet leave us an interesting question: *can we share their charging resources together and achieve a better charging efficiency for the whole charging network*? To answer this question, we first analyze the charging event distributions of the two EV fleets, and then we investigate the existing charging infrastructures for the two EV fleets to investigate if there are enough charging points to satisfy the charging demand of individual fleets. Finally, we found that there are both temporal and spatial opportunities to enhance the overall charging efficiency (e.g., reduce the waiting time) of the e-taxi fleet by sharing the charging infrastructure with e-buses.

Figure 9 shows the charging event distributions of the two EV fleets in 24 hours of a day. We found that there are three charging peaks of the e-taxi fleet, i.e., 1:00-5:00, 12:00-14:00, and 16:00-18:00. For the e-bus fleet, there are only two charging peaks in 12:00-14:00 and 21:00-1:00. Comparing the charging event distributions of the two fleets, we found that they have some common peaks, e.g., 12:00-14:00, which is because both e-taxi and e-bus drivers can have lunch and rest during this low passenger demand period. However, during some other periods, e.g., 16:00-18:00, the e-bus fleet has a lower charging demand, but the e-taxi fleet has a higher charging demand. This is because most e-taxi drivers will have a shift during 18:00-19:00, and they need to return a fully charged e-taxi to their colleagues. This finding provides a temporal opportunity for the shared charging since we can schedule some e-taxis to charge in e-bus charging stations during some e-taxi charging peak durations.

The spatial distributions of the charging stations for the two EV fleets are shown in Figure 10, where yellow circles stand for e-taxi charging stations and blue triangles mean charging stations for e-buses. The sizes of the circles or triangles stand for the number of charging points in each station, e.g., a larger circle means more charging points in this station. We found that most large stations for e-taxis are located in the downtown area, but most large stations for e-buses are in the suburban areas. There is also a distinct difference between the number of the two types of charging stations, i.e., 405 e-bus charging stations vs. 117 for e-taxis. Certainly, we need also consider the number of charging points for the two fleets. There are over 5,000 charging points for e-buses while fewer than 4,000 charging points for e-taxis. In addition, the figure also shows that e-buses charging stations are

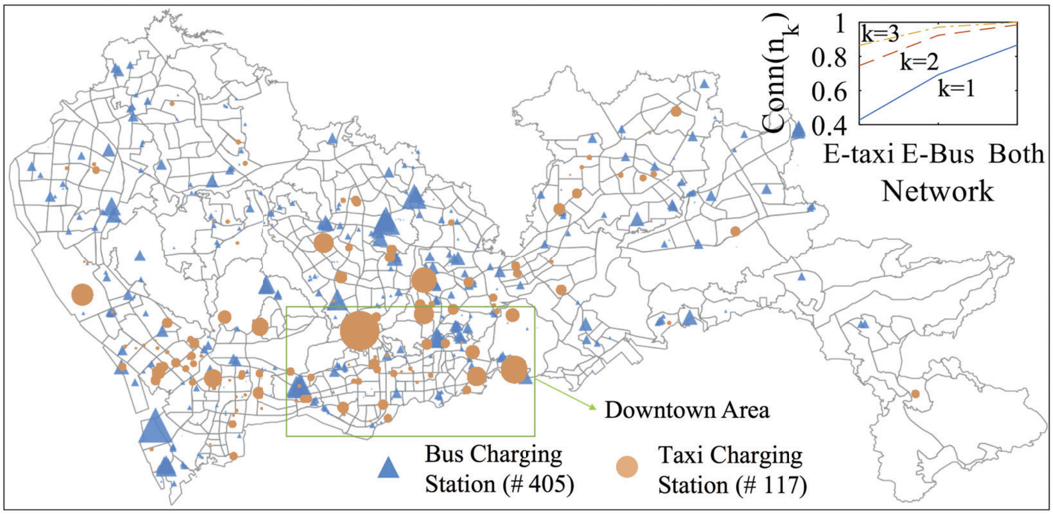


Fig. 10. Charging stations of e-taxis and e-buses.

distributed across the city, but e-taxis charging stations are concentrated in some regions. Hence, we found that there is an unbalanced number of charging stations for the two heterogeneous EV fleets even though the number of charging points are similar.

Based on the above finding of the unbalanced number of charging stations for heterogeneous EV fleets, we further investigate the potential spatial benefits for the e-taxi fleet if it utilizes charging points for e-buses.

Definition 1: We define the *charging network connectivity* for an EV fleet as the percentage of the number of stations that have the nearest charging station in K km among all stations, as follow: where $Conn(n_k)$ is the k connectivity of the charging network n. $CS(k)$ is the number of charging stations which have neighbors in K km. N is the total number of charging stations in this charging network.

$$Conn(n_k) = \frac{CS(k)}{N}, \tag{1}$$

Figure 11 shows the CDF of the distance between charging stations. We found that the charging network connectivity of e-buses is higher than of the e-taxi charging network. The connectivity will be much higher if we combine the two networks together. More specifically, as shown at the top corner of the Figure 10, the 2 connectivity of the e-taxi charging network would increase from 69% to 98% if e-taxis can leverage the charging stations for e-buses, which means that e-taxis can find a nearer charging station easily. Moreover, we also conclude that an e-taxi could find another charging station within shorter distances by considering e-bus charging stations if it reaches a charging station without available charging points.

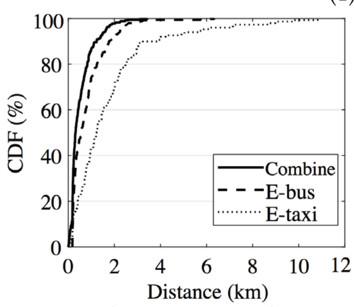


Fig. 11. Charging station distance.

Moreover, all EVs and chargers have the same charging interface standard in China [38], so it is feasible for e-buses and e-taxis to share charging infrastructures. In addition to China, some other countries or regions also have their standards for EV charging, e.g., Europe [31], US [16], etc. A difference between various kinds of charging infrastructures is their charging rates, which can be considered as fast charging mode or slow charging mode for heterogeneous EVs. In some other regions, it is also feasible for EVs to utilize adapters to accommodate different chargers even with different interfaces. Hence, we do not need to rebuild new infrastructures for shared charging of heterogeneous EV fleets, which provides a good realistic opportunity to utilize existing charging infrastructures to improve the overall charging efficiency of heterogeneous EVs instead of spending extra costs for more charging stations.

Based on the above data-driven investigation combined with real-world considerations and field studies (shown in Section 5.1), we conclude that it is practical and beneficial to share charging stations for heterogeneous EV fleets to improve the overall charging efficiency of the urban charging networks.

4 SHAREDCHARGING: SCHEDULING DESIGN

Currently, there are many heterogeneous EVs (e.g., e-buses, e-taxis, and e-trucks), which have various sizes and operating patterns for different purposes. These heterogeneous fleets may be operated by different companies, e.g., two different companies operate e-taxis and e-buses, respectively. Large size e-buses serve people with relatively fixed travel demand and small size e-taxis cruise in a city to satisfy sporadic travel demand. Also, the same company can also have heterogeneous EV fleets, e.g., the United Parcel Service (UPS) has different sizes of e-trucks for package delivery. These heterogeneous fleets may be jointly considered to charge for higher charging efficiency. In this paper, we consider e-taxis and e-buses as concrete examples of our heterogeneous fleets. We provide more discussions on the practicality of shared charging scheduling in Section 6.

4.1 Key Idea of sharedCharging

Before we formulate our problem, we consider a few real-world scenarios for e-buses and e-taxis in Shenzhen as our design guideline as follows. Currently, most e-bus charging stations are deployed in bus terminals, which belong to Shenzhen bus companies. E-buses can only be charged at their own terminals, so their charging demand is more predictable and controllable, even though multiple e-bus lines may share the same bus terminal and thus they can be charged together. In contrast, e-taxis may have charging demand at arbitrary locations because of their stochastic cruising patterns. In Shenzhen, the e-bus charging network and the e-taxi charging network are unconnected, which means that charging infrastructures of e-buses and e-taxis are exclusive for each other and cannot be shared due to logistic reasons.

As a result, the above real-world constraints, along with the unbalanced charging supply deployment and different operating/charging patterns (as we presented in Section 3) result in low charging efficiency for the whole charging network. Hence, in this paper, we envision that heterogeneous EV fleets can share their charging stations, combined with centralized scheduling, to improve their charging efficiency. Intuitively, we can straightforwardly combine the e-bus charging network and e-taxi charging network together. However, in practice, e-buses are much larger than e-taxis, so e-buses need spacious parking lots for them to park and charge, and e-taxi charging stations are normally too small for e-buses to charge. Most importantly, the charging rate of an e-bus charger is 100 kW, and the charging rate of an e-taxi charger is 30 kW, which means the charging time of e-buses in e-taxi charging stations will be over three times than in e-bus charging stations, which make it impractical to schedule e-buses to e-taxi charging stations, and more reasons will be shown in Section 4.3.

Therefore, the **key idea** of sharedCharging is that: (i) we schedule e-taxis to charge in either their own charging stations or in charging stations for e-buses if it achieves better charging efficiency, e.g., reducing charging overhead; (ii) we schedule e-buses to charge in either their own charging stations (i.e., terminals) or serving another line which has a same terminal with its current line and then charge in other bus lines' terminal if it achieves better overall charging efficiency, e.g., reducing charging time for e-taxis or balancing the utilization rates of e-bus charging stations). At the same time, we also guarantee timetables of all e-bus lines, which means sharedCharging will not interrupt the operation of the e-bus fleet.

Our sharedCharging can provide benefits for both the e-taxi fleet and the e-bus fleet. For e-taxis, sharedCharging provides them more places to charge, which can potentially reduce their waiting time at charging stations during charging peak durations and traveling time to charging stations. In addition, the utilization of e-taxi charging stations will be more balanced under sharedCharging scheduling. With sharedCharging, an e-bus can go different terminals to charge instead of staying at the original two stations, which provides more charging location options for e-buses. Moreover, sharedCharging will balance the utilization of e-bus charging stations without disrupting the normal operation of the e-bus fleets, which reduces charging resource waste and increases the utilization rates of e-bus charging stations due to extra charging events from e-taxis. Combining the benefits for e-taxis and e-buses, sharedCharging can improve the overall charging efficiency for heterogeneous EV fleets. More details are shown in the following part of this section.

4.2 Charging Process of Heterogeneous EV Fleets

Suppose there are two large-scale heterogeneous EV fleets in a city, e.g., an e-taxi fleet and an e-bus fleet. We consider the e-taxi fleet has n e-taxis $S_T = \{ET_1, ET_2, ..., ET_n\}$ and the e-bus fleet has m e-buses $S_B = \{EB_1, EB_2, ..., EB_m\}$. There are two sets of charging stations, i.e., e-taxi charging station $CS_T = \{CS_{T_1}, CS_{T_2}, ..., CS_{T_{m1}}\}$ and e-bus charging station $CS_B = \{CS_{B_1}, CS_{B_2}, ..., CS_{B_{m2}}\}$. The number of charging points in each charging station is $|CS_i|$, for $i \in \{T_1, T_2, ..., T_{m1}, B_1, B_2, ..., B_{m2}\}$. The two EV fleets send a sequence of sporadic charging requests $\tau = \{\{R_b\}, \{R_t\}\} = \{\{R_{t_1}, R_{t_2}, ..., R_{t_{r1}}\}, \{R_{b_1}, R_{b_2}, ..., R_{b_{r2}}\}\}$ during their daily operation. For each charging activity of EVs, there are three stages (i.e., *traveling*, *waiting*, and *service*), which can be extracted from GPS data [7, 25, 41].

As shown in Figure 12, an EV sends a charging request at t_0, then it will be scheduled to a charging station and it arrives the charging station at t_1, so $|t_t| = t_1 - t_0$ is the *traveling time* we define in Section 3.2. (Note that in the current situation, e-taxis drivers make scheduling decisions by themselves, which means they will choose where to charge based on their experience.) When it arrives at the charging station at t_1, all charging points may be occupied, so it queues for an available charging point to t_2, and $|t_w| = t_2 - t_1$ is the *waiting time* in Section 3.2. $|t_w| = 0$ if there are unoccupied charging points available when the EV arrives at the charging station. At t_2, the EV will start to charge and finish the charging process by t_3. Then, the time duration from t_2 to t_3 is called *service time*, which is $|t_s| = t_3 - t_2$. The total time of the charging process is $\left|t_p\right| = t_3 - t_0 = |t_t| + |t_w| + |t_s|$.

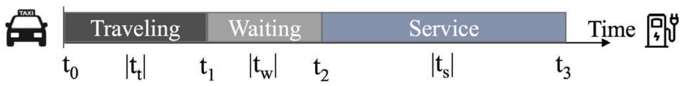


Fig. 12. Charging process of EVs.

4.3 sharedCharging Charging Scheduling

We design a charging scheduling algorithm sharedCharging to enhance overall EV charging efficiency by sharing unconnected charging resources of heterogeneous EV fleets. sharedCharging is developed and solved through transforming the shared charging scheduling into a classical processor scheduling (i.e., two-type heterogeneous multiprocessor real-time scheduling) problem with the self-suspend [4, 33]. CPU/GPU scheduling [19, 21] is an active and popular research direction in the Computer Science field, and many CPU/GPU works can be generalized to other domains. We quantified some similarities between EV charging and multiprocessor scheduling and then leverage effective algorithms for the heterogeneous multiprocessor real-time scheduling to solve it. In the next part, we first introduce the two-type heterogeneous multiprocessor real-time scheduling.

4.3.1 Two-Type Heterogeneous Multiprocessor Real-Time Scheduling. Considering a set of sporadic real-time including n tasks $\tau = \{\tau_1, \tau_2, ..., \tau_n\}$ to be scheduled on a two-type heterogeneous multiprocessors c, which consists of a set of heterogeneous cores, and the collection of cores with the same type is called a *cluster*, so there are two clusters c_1 and c_2 on the two-type heterogeneous multiprocessor. For each cluster c_k, it consists of m_k identical cores of type-k ($k \in \{1, 2\}$) onto which the individual tasks are scheduled. For each task, it may have different execution rates on different clusters, e.g., r_i^1 and r_i^2 in this two-type heterogeneous multiprocessors, where i is the ith task. There are three types of heterogeneous multiprocessors scheduling based on if tasks can be migrated between cores, i.e., *non-migrative*, *intra-migrative*, and *fully-migrative*. Note that among the three scheduling methods, no single task can run on multiple cores at the same time even though the task may migrate. These tasks may *self-suspend* [3, 6, 26] due to shared resource accessing on a multiprocessor platform.

4.3.2 sharedCharging Charging Scheduling Equivalent. Under the heterogeneous EV charging scheduling scenario, we consider a set of sporadic charging requests/tasks τ running on a two-type heterogeneous charging network c, which consists of two types of heterogeneous charging stations, i.e., e-bus charging stations and e-taxi charging stations, which is equivalent to a two-type heterogeneous multiprocessor. Each charging point is considered as a CPU core, so charging points for e-buses and e-taxis are two sets of heterogeneous core clusters c_1 and c_2 with different execution rate r_i^1 and r_i^2. (i) Considering practical situations, drivers would not want to be interrupted when their EVs are charging, so the shared charging scheduling should be *non-preemptive*, which means other later tasks cannot preempt ongoing charging activities. (ii) Since an EV cannot teleport from one charging station to another charging station, the shared charging scheduling should be *non-migrative*. Under non-migrative scheduling, once tasks are assigned to cores, the scheduling problem is reduced to a collection of independent unicore or identical-multicore scheduling problems, which have been well studied and can be solved by existing methods [4, 34]. As we described in Section 4.2, a charging process of an EV includes three stages, which correspond to a suspension stage, another suspension stage, and an execution stage in the heterogeneous multiprocessor real-time scheduling, respectively. A mapping of charging scheduling to multiprocessor scheduling can be found in Table 3.

Table 3. Multiprocessor scheduling vs. charging scheduling.

Charging Scheduling	CPU Scheduling	Charging Scheduling	CPU Scheduling
Charging Station	Processor	Traveling	Suspension
Charging Point	Core	Waiting	Suspension
Charging Rate	Execution Rate	Service	Execution

4.3.3 The Global Earliest Deadline First Algorithm. In this part, we show how we solve the charging scheduling of heterogeneous EV fleets based on a classical method for the heterogeneous multiprocessor real-time scheduling, i.e., Global Earliest Deadline First (GEDF) [40]. We modify GEDF to accommodate and effectively solve our heterogeneous EV charging scheduling problem.

The heterogeneous multiprocessor real-time scheduling includes two stages [33]: (i) assigning tasks to each processor and (ii) performing uniprocessor scheduling on each processor once tasks are assigned to processors. For the latter problem, it has been well-solved by using EDF algorithm [7], where the non-preemptive issue is also addressed. Since EVs have no deadlines, we set the charging finish time as the scheduling deadline. Then, for the first problem, since in two-type heterogeneous multiprocessor scheduling, a task can be scheduled to any processor, and the heterogeneous multiprocessors have different execution rates r_i^1 and r_i^2, so one task has different finish times. However, in our charging scheduling, e-buses can only charge in e-bus charging stations due to real-world charging space limitation. In a real-world charging scenario, the charging rate of e-buses charging station is 100 kW, and the charging rate of e-taxis is 30 kW, which means the charging service time of e-buses in e-taxi charging stations will be over 3 times than in e-bus charging stations. It means that e-bus charging tasks will always be scheduled to the high execution rate processor under GEDF, which is the equivalent of the e-bus charging network. In that case, we can keep the constraint that e-buses only charge in e-bus charging stations. Hence, we utilize a modified GEDF algorithm with the corresponding mapping to effectively solve the heterogeneous EV fleets scheduling problem.

For our modified GEDF, which is more efficient than the standard GEDF. Specifically, our modified GEDF can address problems with asymmetric compatibility. For example, in our heterogeneous EV scheduling scenario, e-taxis can charge in both e-bus and e-taxi charging stations, while e-buses can only charge in e-bus charging stations. A direct benefit is that the algorithm's search space for charging requests from e-buses could be reduced, so our algorithm is faster than the standard GEDF, which makes our algorithm more practical for real-time scheduling even with large-scale EVs.

4.3.4 sharedCharging Charging Scheduling Decisions. In this part, we show how we share charging infrastructure of different EV fleets to achieve a better social benefit without damaging either of the fleets under the heterogeneous multiprocessor real-time scheduling with a self-suspend scenario.

In this work, we focus on the real-time charging scheduling for heterogeneous EV fleets, considering some real-world constraints, e.g., spaces in charging stations, charging rate difference, and the availability of charging points in charging stations. Our sharedCharging can schedule e-taxis to charge in e-bus charging stations if it can reduce charging overhead of e-taxis, and e-buses can also be rescheduled to charge in other e-bus lines' charging stations if they share the same terminal. We estimate the reachability of e-buses to other charging stations by considering their real-time battery levels and the expected energy consumption on different lines, which is related to road lengths, traveling time, and traffic and can be predicted with the historical and real-time GPS records [10, 11, 44, 48, 53].

As shown in Figure 13, e-bus line L_1 and line L_2 share the same terminal/charging station CS_{B1}, and there are many e-buses serving for the two lines. Currently, EB_1 can only charge in CS_{B1} and CS_{B2}. E-taxis ET_1 can only charge at taxi charging stations CS_{T1} and CS_{T2}. However, under our sharedCharging scheduling, we can schedule e-taxis to charge in e-bus charging stations and e-buses can be rescheduled to charge in other e-bus lines' charging stations if they share some same terminals. For example, we can schedule ET_1 to charge in CS_{T1}, CS_{T2}, CS_{B1}, CS_{B2}, and CS_{B3}. For EB_1, sharedCharging can also schedule it to serve line L_2 and then charges in CS_{B3}. Since both charging requests/tasks of e-buses and e-taxis arrive in an online fashion, sharedCharging schedules the charging task of e-taxis and e-buses one by one. All scheduling decisions will be based on the charging tasks' arrival time, i.e., *first come first serve (FCFS)*. We do not utilize the batch scheduling for better performance because it is impractical to let e-taxi drivers stop there and wait for our scheduling decisions.

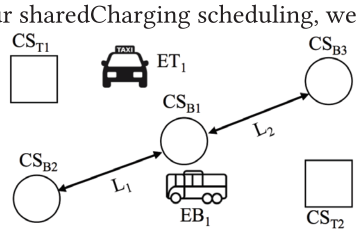


Fig. 13. Charging scheduling.

After receiving a charging task, sharedCharging will schedule a charging point (i.e., equivalent of a CPU core) for it, and then the charging point will suspend until the EV plugs in a charging point. During the whole charging process, the charging point will be occupied by this EV and cannot be preempted until it finishes charging. The traveling time $|t_t|$ of an EV EV_x is decided by the distances and traffic conditions to charging stations. The waiting time $|t_w|$ is related to the number of EVs under charging, the number of queuing EVs in front of EV_x at this station, and the number of charging points $|CS_i|$ in this station. In the worst case, all charging points are occupied and there are some EVs queuing in front of EV_x, so it needs to wait for an EV fully charged and to leave. Note that it is theoretically impossible for scheduling more than $|CS_i|$ vehicles to a station due to the long charging duration of EVs, and it is also consistent with our observations, so the waiting time of EV_x is bounded by $max(|t_s|)$ of EVs which are charging in this station, which means that EV_x can definitely obtain an unoccupied charging points once the EV in front of EV_x with the longest charging service time gets fully charged and leaves. The charging service time $|t_s|$ is decided by the remaining battery level of EV_x and the charging rate r of the charging points.

(a) Scheduling Decisions for E-buses: Since e-buses usually have fixed timetables to satisfy passengers' travel demand and they can only charge at their terminals, so they always have relatively stable and controllable charging plans, and it is easy to estimate the charging time for each e-bus [44]. Under sharedCharging charging scheduling, each e-bus has three charging scheduling decisions when they have a charging request in a charging station:

(1) Charging at the current station, e.g., EB_1 charges at CS_{B1};
(2) Serving its original line L_1 and charges in another terminal of this line, e.g., EB_1 charges at CS_{B2};
(3) Serving another line that shares the same terminal with L_1 and then charging in another terminal of the new line, e.g., EB_1 serves a new line L_2 and then charges at CS_{B3}.

Taking EB_1 for example, the decision (i) is the normal scheduling for it. Since this decision follows the prefixed schedule, the timetable is always guaranteed. The decisions (ii) and (iii) are made when an e-taxi can have shortest charging overhead if it leverages the e-bus charging point for EB_1, so the e-bus will go to another charging station to charge and leave the charging points for e-taxis. Another constraint for (ii) and (iii) is that there must be another e-bus in this terminal that can replace the operation of EB_1 to guarantee the timetable of the line L_1. If both (ii) and (iii) are available, we prioritize the EB_1 to serve its original line to reduce the impact on the bus network. More importantly, we leverage the energy difference to break the tie if multiple lines are available under the decision (iii), which means we schedule the e-bus to serve the line with the least energy consumption since it may relieve the "range anxiety" of e-bus drivers and ensure the e-bus can arrive the new charging station. Hence, all e-bus lines' timetables are guaranteed, i.e., the real-time requirement is satisfied, and the service quality of the e-bus network will not decrease.

(b) Scheduling Decisions for E-taxis: There are three different scheduling decisions for an e-taxi charging request under sharedCharging scheduling:

(1) Scheduling an e-taxi to an e-taxi charging station and achieving the optimal performance, e.g., the minimum charging overhead (i.e., the earliest deadline). For example, if ET_1 has a charging request near CS_{T1} and there are charging points available in CS_{T1}, sharedCharging will schedule ET_1 to charge in CS_{T1}.
(2) If CS_{B1} can bring the smallest charging overhead for ET_1, and there are unoccupied charging points in CS_{B1}, we then estimate the accessibility of the charging stations during the charging period of ET_1 based on predictable charging plans of e-buses in CS_{B1}. If there are charging points available in CS_{B1} during the charging duration of ET_1, sharedCharging then schedules it to charge in CS_{B1}, but if there are some e-buses need to charge in CS_{B1}, e.g., EB_1 for line L_1 is waiting in CS_{B1} for charging but this station is the optimal charging choice for ET_1, we then check if EB_1 has enough energy to serve line L_1 and then charge in CS_{B2}. If there are no charging points available in CS_{B2} or the battery capacity of EB_1 is insufficient for L_1, sharedCharging will continue to search for other shorter lines that share the same terminal with L_1, e.g., line L_2, to decide if the remaining energy of EB_1 is sufficient for serving L_2 and there are unoccupied charging points in CS_{B2}. If the above candidate lines exist, we still cannot directly schedule EB_1 to these lines since one of the most important constraints for e-bus scheduling is the timetable guarantee, i.e., the real-time requirement for serving passengers. If there are e-buses for L_1 or L_2 can replace EB_1 to serve L_1, then we schedule EB_1 to serve L_2 and keep the timetable of L_1. Only all the above constraints satisfy, sharedCharging will schedule ET_1 to charge in CS_{B1}, which minimizes the charging overhead of ET_1 while keeping the timetables and charging efficiency of the e-bus network.
(3) If it is not feasible to schedule ET_1 to charge in CS_{B1}, sharedCharging will further estimate the charging deadline for ET_1 in other charging stations (e.g., CS_{T2}, CS_{B2}, or CS_{B3}), and then schedule it to a charging station with the minimum charging overhead considering above constraints.

In summary, the scheduling process of sharedCharging can be seen as Algorithm 1.

Algorithm 1: sharedCharging Charging Scheduling

Input: Charging Requests τ;
Output: Charging Stations CS_T, CS_B

1 **foreach** $\tau_i \in \tau$ **do**
2   **if** $\tau_i \in R_b$ **then**
3   **if** *no interaction from* R_t **then**
4   charging in its own station $CS_{B_{k1}}$ with the earliest deadline;
5   **else if** *another feasible* CS_{Bk2} *has the earlier deadline than* $CS_{B_{k1}}$ **then**
6   scheduling it to $CS_{B_{k2}}$;
7   **else**
8   still charge in $CS_{B_{k1}}$;
9   **end**
10   **end**
11   **if** $\tau_i \in R_t$ **then**
12   **if** $CS_{t_{m1}}$ *has the earliest deadline* **then**
13   scheduling it to $CS_{t_{m1}}$;
14   **else if** $CS_{B_{k1}}$ *has the earliest deadline* **then**
15   **if** $CS_{B_{k1}}$ *is available based on all constraints* **then**
16   scheduling it to $CS_{B_{k1}}$;
17   **else**
18   find other possible optimal $CS_{B_{ki}}$ or $CS_{T_{mj}}$, and go back to step 11;
19   **end**
20   **end**
21 **end**

4.3.5 *Remarks on Design Choices.*

In our sharedCharging design, we consider many real-world constraints, which we learned from our communications with heterogeneous EV fleets operators and governments.

(i) We implicitly consider e-taxi drivers' charging preference, i.e., we only schedule e-taxis when they have charging requests. According to NYC Taxi & Limousine Commission [5], an ideal e-taxi program should cause minimal disruption to the industry since it has chosen many of its current practices based on years of practice and learning about what works well and what does not work well in a real-world setting. If we change the charging time or behaviors of drivers, it may affect the entire taxi system and possibly change drivers' daily life, e.g., the arranged charging time conflicts with drivers' daily schedule, resulting in the low participation of the scheduling system. As a result, we only schedule e-taxi drivers to the corresponding charging stations after they submitted charging requests for practical considerations.

(ii) Even though we consider real-world charging requests, some e-taxis drivers will still choose charging stations based on their experience instead of following our scheduling. For example, if an e-taxi driver lives near a charging station, the driver would still go to this station and get some rest during the charging process, even if sharedCharging schedules it to another station with the shortest waiting time. As a result, we evaluate the scheduling performance under difference drivers' participating rates in Section 5. However, for e-buses, we can schedule them to serve any lines since they always follow centralized management. The only issue we need to consider is to guarantee their timetables if we need to change their original charging plans, which we have already addressed in Section 4.3.4.

(iii) We did not schedule e-buses to charge in e-taxi charging stations since the space of e-taxi charging stations is not enough for e-buses to park and charge, which can be seen from the field studies in Section 5.1 and the charging rate of e-taxi chargers is too low for e-buses and causing three times of charging durations. Even so, our scheduling strategy can be extended to the case that e-buses can share the e-taxi charging stations with some constraint relaxation if the charging time and parking spaces were not considered.

(iv) For a practical real-world reason, we envision that the e-taxis charging in bus charging stations will still keep the charging rates for e-taxis (i.e., 30 kW) instead of the 100 kW for e-buses even though high charging rates can reduce the charging time for e-taxis. This is because it will accelerate the battery attenuation if the charging rates are too high [35].

5 EVALUATION

In this section, we extensively evaluate the performance of our sharedCharging based on the data from two heterogeneous EV fleets in Shenzhen. We compare sharedCharging with the Ground Truth and some state-of-the-art baselines. We mainly show the charging overhead of the e-taxi fleet under different scheduling strategies and the charging resource balance effect of our sharedCharging. Finally, we also compare the system performance under different driver participation rates.

5.1 Field Studies

During the project, we have conducted a set of field studies to identify real-world charging issues and verify the patterns we found. Figure 14 shows charging scenarios of e-taxis and e-buses in Shenzhen, we found that the e-bus charging station has enough space for e-buses and e-taxis to park and charge, but the space in a typical e-taxi charging station is not enough for e-buses. There is always a long queuing line at noon in this e-taxi charging station (BYD Baishizhou Charging Station), and e-taxi drivers normally need to wait more than 30 minutes. These field studies help us better understand the real-world issues, the potential impacts of our study, and the implication of our scheduling.

(a) E-taxi Charging Station (b) E-taxi Queuing Line (c) E-bus Charging Station

Fig. 14. Field studies in Shenzhen.

One lesson we learned from our field studies is that during the rapid EV promotion process, even though the charging infrastructure is increasing, the number of charging points for e-taxis is still far from the objective. In addition, most new e-taxi drivers are not familiar with the locations of charging stations, and their heuristic charging behaviors always cause a long waiting time for them. Deploying more charging stations for EVs may effectively address this problem, but the extremely high land price in Shenzhen makes it expensive to build charging stations, e.g., a charging station for e-taxis near the downtown areas will cost more than 100 e-taxis based on our interactions with the charging station providers. As a result, effective charging scheduling is more practical than building new charging stations, so our shared scheduling is better for current EV operation.

5.2 Experimental Setup

Data Management: 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. Due to large-scale EV 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.

Evaluation Data: As introduced in Section 2, we utilize streaming GPS records generated by over 16,000 e-buses and 13,000 e-taxis from the Chinese Shenzhen city, combined with data of over 500 charging stations.

Baseline Setting: To show the effectiveness of our real-time charging scheduling for heterogeneous EV fleets, we compare our sharedCharging with Ground Truth and a set of baselines, including (i) *OCSD* in [25] (i.e., Nearest Distance scheduling Only considering Taxi charging stations (NDOT)); (ii) Nearest Distance scheduling With considering Bus charging stations (NDWB); (iii) *REC* in [7] (i.e., Shortest Waiting time scheduling Only considering Taxi charging stations (SWOT)); (iv) *Recommender* in [41] (i.e., Shortest (traveling + waiting) Time scheduling Only considering Taxi charging stations (STOT)), which is the optimal scheduling considering only taxi charging stations; (v) shortest (traveling + waiting) time scheduling, which only considers scheduling e-taxis to bus charging stations but not scheduling e-buses to other terminals (sharedCharging$^-$).

Evaluation Metrics: The objective of our sharedCharging is to increase the charging efficiency of the whole charging network, which includes two parts, i.e., reducing the charging overhead for the e-taxi fleet and balancing the charging demand of all charging stations. Hence, we utilize different metrics to measure the system performance, including (i) traveling time, (ii) waiting time, (iii) total charging overhead, (iv) total charging overhead decrease, and (v) charging station occupation rate. The traveling time $|t_t|$ and waiting time $|t_w|$ have been described in Section 3. The total charging overhead of the nth charging event can be formulated as:

$$\left|t_p^n\right| = \left|t_t^n\right| + \left|t_w^n\right| + \left|t_s^n\right|, \tag{2}$$

Definition 2: We define the daily (or hourly) *Charging Station Occupation Rate (CSOR)* of a station s_i to quantify the average occupation time of each charging point in the station, which is described as:

$$CSOR\left(s_i\right) = \frac{\sum_{j=1}^{|s_i|} CT\left(s_i^j\right)}{|s_i|}, \tag{3}$$

where $CT(s_i^j)$ is the daily (or hourly) occupation time of jth charging point s_i^j in the station s_i; $|s_i|$ is the number charging points in station s_i. To balance the charging station utilization, we need to reduce the number of charging stations with very low and very high *CSOR* since a very low *CSOR* means resource waste and a very high *CSOR* means potential longer waiting time in those stations.

Simulation Setup: We adopt a rolling horizon manner to conduct the simulation, which is widely utilized in the vehicle mobility intervention research, e.g., order dispatching of for-hire vehicles [45, 49]. The basic idea of the rolling horizon manner is that we will update the status of all charging stations after scheduling a vehicle, and then the next decision is made based on the updated information. Each charging event, instead of a vehicle, is modeled as an agent for simulation so that charging events can be considered independent [7, 41]. We make a scheduling decision after receiving a charging request, so we can handle each charging request no matter when and where it occurs based on its real-time status and the updated information. The charging point will be suspended (i.e., occupied) once it has been assigned to an EV, so it will not be assigned to other EVs before the assigned EV finishes charging.

5.3 Charging Overhead of E-Buses

For all e-buses, since they are already under centralized charging management and their charging plans are controllable, so we assume that they will always send charging requests after they arrive at their terminals because they can not charge during operating durations with passengers on board. In this case, the traveling time of e-buses is 0 if they charge in their own terminals. If an e-bus serves another line and charges in other bus lines' terminals, they will operate on the new line for picking up passengers. In this case, we also consider its traveling time is 0 since it will not waste time from its current location to another charging place. However, for e-taxis, they will not serve passengers when they travel to charging stations, so e-taxis need extra traveling time for charging.

In our sharedCharging, e-buses have a higher priority to utilize e-bus charging stations, so the charging of e-taxis happening in e-bus charging stations are built on without impairing e-buses' performance. The reason for the higher priority of e-buses is that they have timetables to follow for satisfying bus passengers. Since timetables of all e-bus lines are guaranteed, and we always schedule them to charge when they have no operating tasks, so we consider the waiting time of e-buses is 0 due to their abundant charging resources and controllable charging schedule. This is a difference between e-buses and e-taxis since e-taxi drivers always try to maximize their operating time for more profits, and their current charging mode is not centralized managed. Since both the traveling time and waiting time of e-buses are considered 0, so we do not show the performance of them.

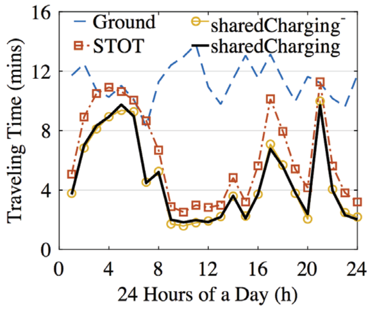


Fig. 15. Average traveling time of e-taxis.

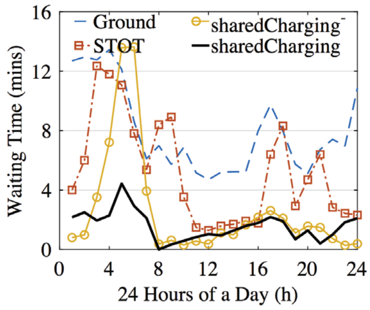


Fig. 16. Average waiting time of e-taxis.

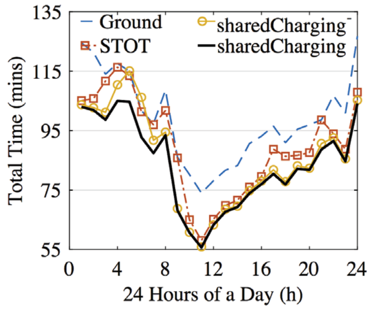


Fig. 17. Average total charging time for a charge of e-taxis.

5.4 Charging Overhead of E-Taxis

Figure 15, Figure 16, and Figure 17 show the average traveling time, average waiting time, and the average total charging time of each e-taxi charge under different scheduling methods. Although we found that NDWB has the shortest traveling time, followed by NDOT, with about 8 minutes shorter than the Ground Truth, they will have a very long waiting time during peak hours, resulting in very poor performance. This is because, under the shortest distance scheduling, many drivers are scheduled to the same charging stations due to their operation nature, resulting in longer waiting time, so we do not show their performance in the three figures. Our sharedCharging⁻ and sharedCharging achieve similar performance, with 39% reduction compared with Ground Truth and better than STOT. From Figure 16, we found our sharedCharging achieves the best performance regarding the waiting time, with a 63.5% reduction compared with Ground Truth and a 48.7% reduction to STOT. Compared sharedCharging⁻ with sharedCharging, we found that sharedCharging⁻ will result in longer waiting time for e-taxis during 4:00-6:00 even though shorter waiting time during the midnight. We found that there is a charging peak for the e-taxi fleet about 4:00 as shown in Figure 9, which indicates our sharedCharging can effectively reduce waiting time for e-taxis during their charging peak durations. From Figure 17, we found that our sharedCharging can achieve the best performance for reducing the charging time of e-taxis.

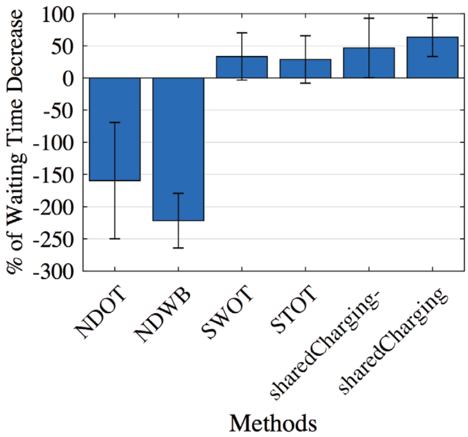


Fig. 18. Waiting time decrease.

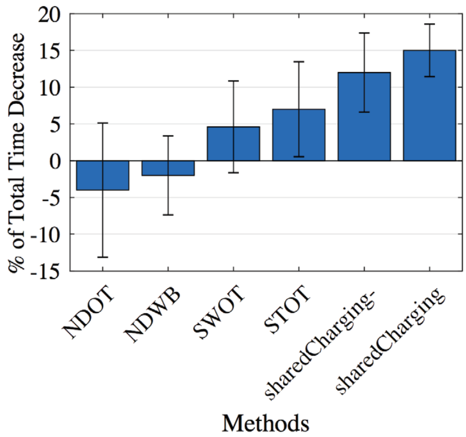


Fig. 19. Total charging time decrease.

We also show the average waiting time and total charging time reduction with their standard deviations, as shown in Figure 18 and Figure 19. We found that sharedCharging reduces about 15% (16 mins) total overhead for each charge of e-taxi drivers, which is twice of the improvement of STOT. We found that the NDOT and NDWB have worse performance than Ground Truth because of their long waiting time. SWOT has worse performance than STOT due to prolonged traveling time. In addition, we found that all scheduling methods include variances with different degrees, which means the benefits for different drivers are various, and our sharedCharging achieves a relatively smaller deviation than other methods.

5.5 Spatial Distribution of Charging Events

We leverage the *Charging Station Occupation Rate* to describe the spatial distribution of charging events. Figure 20 and Figure 21 show the e-bus and e-taxi charging station occupation rates. The x-axis is the daily charging station occupation rate, and the y-axis is the percentage of charging stations. We found that the percentage of e-bus charging stations with low occupation rate decreases significantly by leveraging our sharedCharging, e.g., the percentage of e-bus charging stations with occupation rates less than 2 has decreased from 27% to 11%, and other occupation rates are more balanced. Since some e-taxis will be scheduled to the e-bus charging stations, the total occupation rate of the e-bus charging network has increased. From Figure 21, we found that the total occupation rate of the e-taxi charging network has decreased, but it becomes more balanced, e.g., most e-taxi charging stations have occupation rate from 2-7, accounting for over 80%. The percentage of e-taxi charging stations with occupation rate 1 has decreased from 15% to 5% by our sharedCharging. Hence, our sharedCharging effectively balances the demand for different charging stations.

We also show the occupation rates of all e-bus and e-taxi charging stations during different hours. Figure 22 and Figure 23 show the actual hourly CSOR of e-buses and e-taxis. Figure 24 and Figure 25 show the performance of our sharedCharging. The x-axises of Figure 22 to Figure 25 stand for 24 hours of a day, and the y-axises mean the occupation rate distributions of all e-taxi charging stations or e-bus charging stations. We found that the occupation rates of e-bus charging stations are high during midnight. For the e-taxi fleet, it has two time slots with very high charging station occupation rates, i.e., 3:00-7:00 and 17:00-19:00, and both of them are during their charging peak durations. As shown in Figure 24 and Figure 25, the occupation rates of e-bus charging stations will increase while the occupation rates of e-taxi charging stations will decrease under our sharedCharging scheduling, especially during the two charging peak durations of e-taxis. Due to the heuristic charging behaviors

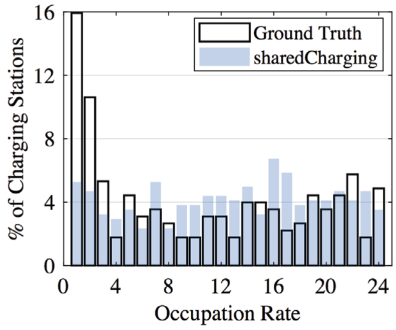


Fig. 20. E-bus daily CSOR comparison.

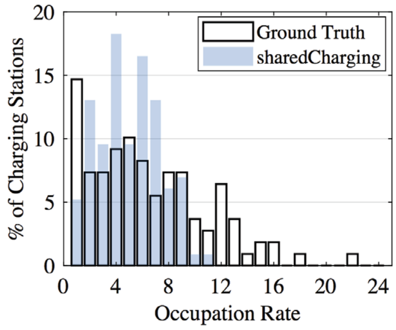


Fig. 21. E-taxi daily CSOR comparison.

of e-taxi drivers, the waiting times of e-taxis may significantly increase during charging peak durations, while our sharedCharging can effectively address this issue.

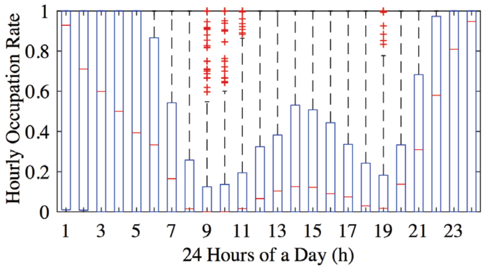


Fig. 22. E-bus hourly CSOR of Ground Truth.

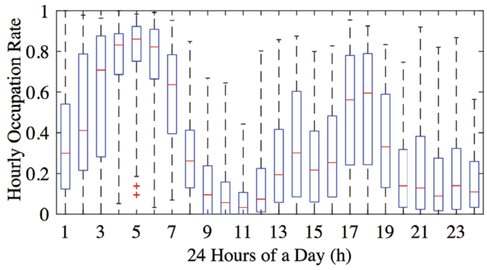


Fig. 23. E-taxi hourly CSOR of Ground Truth.

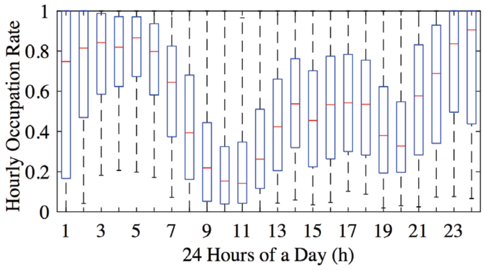


Fig. 24. E-bus hourly CSOR of sharedCharging.

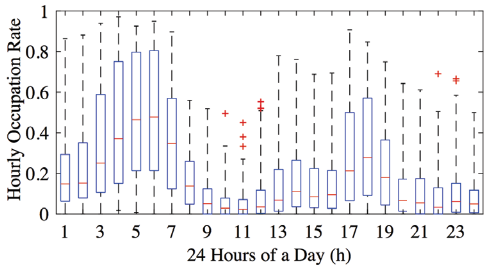


Fig. 25. E-taxi hourly CSOR of sharedCharging.

5.6 Performance Under Different Driver Participation Rates

We consider all e-taxis will follow our scheduling advice in the above investigation. However, in a real-world scenario, some e-taxi drivers will always go to their preferred charging stations even though a shorter time of the scheduling strategy. Hence, we investigate the scheduling performance if only a part of e-taxi drivers follows our scheduling decisions. Figure 26 and Figure 27 show the percentage reduction of traveling time and waiting time under different driver participation rates. We do not show the performance of our sharedCharging^{-} since it has similar performance with sharedCharging. Since NDOT and NDWB have a bad performance, we also do not show them. We found that our sharedCharging always has better performance than STOT, but the performance has a large decrease if over 50% of drivers do not follow our scheduling. Suppose there are about 80% of drivers follow our sharedCharging scheduling because it can reduce their charging overhead, our sharedCharging has the potential to reduce 30% of traveling time and 53% of the waiting time on average for each charging activity. The performance of our sharedCharging is always better than STOT.

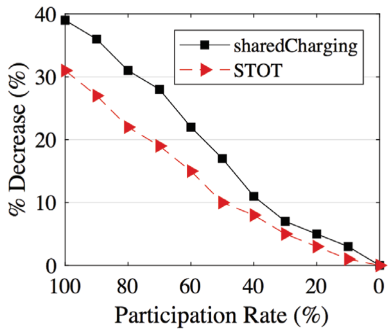


Fig. 26. Traveling time decrease under different driver participation rates.

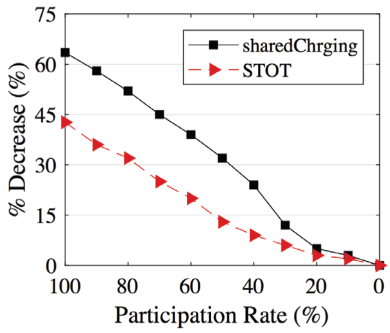


Fig. 27. Waiting time decrease under different driver participation rates.

6 DISCUSSION

In this section, we first summarize a few insights and lessons learned during the project. We then discuss some limitations and potential benefits of our work.

6.1 Insights and Lessons Learned

- **Unbalanced Charging Demand & Supply.** From our data-driven investigation and field studies, we found that heterogeneous EV fleets have unbalanced charging station allocation and unbalanced charging demand & supply. The charging peaks of e-taxis potentially prolong their waiting time in charging stations.
- **Charging Scheduling for Heterogeneous EV Fleets.** We found the heterogeneous EV shared charging scheduling problem can be mapped to a classical CPU scheduling problem (i.e., two-type heterogeneous multiprocessor real-time scheduling) after quantifying their similarities. This effort potentially extends our understanding of real-time multiprocessor scheduling algorithms.
- **Possible Behavioral Changes.** E-taxi drivers and e-bus drivers may change their operating and charging behaviors due to the shared charging strategy. E-taxi drivers will have lower "range anxiety" since more available charging resources and more denser charging networks. E-taxi drivers may go to e-bus charging stations to charge and change their previous charging locations and time durations. E-bus drivers may also need to change their served lines to benefit e-taxis, so they have the potential to serve multiple lines per day. The charging locations of e-buses may also be changed. However, the utilization rates of e-bus charging stations will increase and be more balanced. These behavioral changes need to be further investigated after the sharedCharging deployed in the real world.

6.2 Limitations

- **Practicality of Shared Charging Scheduling.** In this paper, we envision that we can jointly schedule e-taxis and e-buses together. This shared scenario is feasible in many cities where taxi companies and bus companies are overseen by a joint committee, e.g., Shenzhen Transport Committee, which can perform such shared scheduling for both buses and taxis. Even though for cities that taxis and buses are operated separately by competing companies without any incentive for them to perform shared scheduling, our sharedCharging is still useful for single companies that owning heterogeneous EVs with different operating patterns and charging patterns, e.g., logistics companies like UPS, given the trend of vehicle electrification and their diverse business models.
- **Implementation in Other Cities.** The vehicular networks in different cities typically have different operating patterns due to geographic and demographic features, so it is extremely significant to implement sharedCharging in different cities. In this paper, we only use the data from the Chinese Shenzhen city, and we are in the process of obtaining heterogeneous EV data from other cities for comparative investigation at a city level. However, since only Shenzhen has such large-scale e-taxi and e-bus networks, it is difficult to find such large heterogeneous EV fleets 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 EV network to vehicular networks in other cities for a "what if" investigation. For example, what if all conventional taxis and buses in New York City or Beijing were replaced by e-taxis and e-buses, how can we schedule heterogeneous EV fleets for shared charging to reduce the charging stations needed and enhance the overall social welfare. It opens some very interesting research directions.
- **Shared Charging with Other Types of Electric Vehicles.** We only perform the sharedCharging using data from e-taxis and e-buses, while other EVs (electric private vehicles, electric trucks) have not been considered due to some data access issues, but we argue our sharedCharging is generalizable for other fleets because of the data-driven characteristic. We are trying to obtain data of electric private vehicles and electric trucks. In the future, we will consider sharing charging resources for other types of EVs in a city to verify and enhance our sharedCharging, which paves the way for shared charging of future shared autonomous electric vehicles.

6.3 Potential Benefits

- **Electric Vehicle Promotion.** A key obstacle for large-scale EV promotion is the complicated charging issue [43, 50], e.g., inadequate charging infrastructures, unbalanced charging resource allocation and intensive charging peaks. Our design provides an approach for heterogeneous EVs to share charging resources for a higher charging efficiency, which can help other cities or companies to find the possibility to promote heterogeneous EVs. In addition, our work also has the potential for city governments and companies to estimate how many charging points are sufficient for them if all their vehicles are replaced by EVs, which is beneficial for achieving successful large-scale EV promotion.
- **Shared Autonomous Electric Vehicles.** In the vision of smart cities, all vehicles could be shared autonomous EVs in the future [1, 13, 37]. The *large size* of vehicles can be shared by a group of passengers with *fixed travel demand*. For example, autonomous shared e-buses can be used to serve customized lines for commuters since e-buses have a larger capacity so it will be efficient than small vehicles and can also reduce the number of vehicles. For people's *sporadic travel demand*, there will be some *small vehicles* for these stochastic requests. This kind of mobility strategy is similar to current e-taxi operation. Hence, we believe our sharedCharging has the potential to provide some guidelines for shared charging of future shared autonomous EVs.

7 RELATED WORK

There are two different charging scheduling strategies for EVs, i.e., centralized and decentralized ones [18, 24, 47]. Among existing EV charging research, most of them aim to optimize single EV fleets, while some others cooperatively optimize multiple heterogeneous EV fleets. Based on the two dimensions, the EV charging research can be divided into four different categories, which we show in Table 4.

Table 4. Categories of related work.

Scheduling	Homogeneous Fleet	Heterogeneous Fleets
Decentralized	[7, 25, 39, 41, 43, 50]	[14, 15, 22, 29, 30, 36]
Centralized	[18, 20, 23, 24, 44, 52]	*sharedCharging*

7.1 Decentralized Scheduling

Homogeneous Fleet: The decentralized charging scheduling of electric vehicles has been widely studied by many researchers, but most of them are for single homogeneous electric vehicle fleets, e.g., e-bus fleets or e-taxi fleets. Tian et al. [41] design a recommendation system for e-taxis to reduce the total charging time cost for each driver. Li et al. [25] develop a framework for charging station deployment and charging point placement framework to minimize the overall charging time of e-taxis. Yan et al. [50] provide a charger deployment scheme that maximizes the probability of picking up passengers for e-taxis and minimizes the deployment cost. They aim to schedule e-taxis or find the optimal locations to deploy charging infrastructures for e-taxis for reducing the operating cost or charging station deployment cost. Dong et al. [7] develop a real-time EV charging scheduling framework for e-taxi fleets, which informs each e-taxi driver at runtime when and where to have a charge.
Heterogeneous Fleets: Gusrialdi et al. [15] develop a distributed scheduling and cooperative control algorithm for charging of electric vehicles at highway service stations. However, it only considers local information about neighboring charging stations, which may result in suboptimal scheduling compared with centralized scheduling. Kong et al. [22] design a distributed market mechanism to improve the economic and the temporal efficiency of EV demand response. However, all these works have no real-world data and did not capture the different charging patterns of heterogeneous EV fleets.

7.2 Centralized Scheduling

Homogeneous Fleet: There are some research efforts for the centralized scheduling of single EV fleets. Kang et al. [18] propose a population-based heuristic approach to minimize the total charging cost. Kong et al. [23] propose an effective charging rate control algorithm to optimize the social welfare of EVs. However, it does not consider the differences in charging patterns between heterogeneous EV fleets.
Heterogeneous Fleets: Different from existing works, our sharedCharging has a data-driven nature, which is based on the differences in charging patterns between heterogeneous EV fleets after extensive data analyses. Moreover, sharedCharging considers a set of real-world constraints when making scheduling decisions, which make our sharedCharging more practical for real-world implementation and application.

7.3 Summary

Few existing works focus on shared charging scheduling of heterogeneous EV fleets mainly because of no available real-world data to capture their different charging patterns and its complexity. To our best knowledge, sharedCharging is the first work of data-driven real-time scheduling for heterogeneous EV fleets. Such a data-driven investigation and centralized scheduling enable us to identify the real-world charging patterns of heterogeneous EV fleets and design optimal scheduling, which is challenging to reveal using homogeneous EV fleet data or under a decentralized setting.

8 CONCLUSION

In this paper, we conduct, to the best of our knowledge, the first study for real-time shared charging scheduling of heterogeneous EV fleets based on their different charging patterns. We design a system called sharedCharging aiming to improve the charging efficiency of the overall charging network, e.g., reducing charging overhead and balancing charging resource utilization. More importantly, we take the e-bus and e-taxi fleets as a concrete example of heterogeneous electric vehicle fleets. We implement and evaluate sharedCharging based on data of over 16,000 e-buses, 13,000 e-taxis, and over 500 charging stations from the Chinese city Shenzhen. The evaluation results show that our sharedCharging outperforms the ground truth by 63.5% and outperforms a baseline method by 48.7% regarding the waiting time of the e-taxi fleet without disturbing e-buses' timetables. For the immediate benefit, sharedCharging can reduce the charging overhead for the Shenzhen e-taxi network and improve the charging efficiency of the overall charging network. For the long-term benefit, our results in sharedCharging may be leveraged for other cities to operate heterogeneous EV fleets and pave the way for charging scheduling of future shared autonomous EVs.

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