Uncovering the charging behaviors and preferences of electric taxis: A case study of Shenzhen

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Short summary

The rapid development of electric vehicle (EV) has driven the electrification of taxis in several major cities, which also brings a challenge to the charging infrastructure planning. Understanding the drivers' charging behavior is crucial for optimizing infrastructure planning and improving charging efficiency. In this paper, we analyze the charging behavior characteristics of a fully electrified taxi fleet in Shenzhen, China, based on taxi GPS data and public station data. Specifically, we classify stations into commercial stations dedicated to taxi services and public stations available for all vehicles. By leveraging the trajectory and the station data, we identify charging activities and estimate the real charged energy, thereby constructing the state-of-charge (SOC) trajectories. Our results reveal that charging at commercial stations and at public stations exhibits different spatiotemporal characteristics. Although partial charging occurs at both types of stations, it is more often observed at public stations. Besides, taxis operate with battery levels above 50% for most of the time. We further classify charging stations based on their nearby POI and uncover several classes of charging stations that are more appealing to drivers. These findings provide valuable insights into charging infrastructure planning aiming at efficient utilization of charging resources.
Keywords: Charging behavior; Electric taxis; Public and commercial charging stations

1 Introduction

In many large metropolitan areas, ride-hailing vehicles have been fully electrified due to policy incentives (Lei et al., 2022). For example, by 2020, Shenzhen had completely electrified its taxi fleet (Shenzhen Municipal Transportation Bureau, 2021). Long daily travel distance and limited battery capacity of electric ride-hailing vehicles lead to more frequent utilization of the public charging infrastructure (Moniot et al., 2022), imposing substantial challenges on the charging infrastructure. Therefore, understanding their charging patterns, including where and when they recharge and the corresponding charging demand, is crucial for optimizing charging infrastructure planning (Jia et al., 2012; H. Wang et al., 2021).

The charging behavior has drawn much attention in recent research, with particular focus on the spatiotemporal charging patterns and charging station choice. Existing studies on this topic can be broadly divided into two categories: model-based approaches and data-driven analyses. Model-based methods typically rely on assumptions about driver behavior. For example, equilibrium models have been developed to characterize the behavior of selfish drivers who optimize individual utility, including factors like waiting time and charging cost (He et al., 2014, 2015; Chen et al., 2020). However, such approaches require that drivers have perfect information about their own utilities and usage of all charging stations, which is hardly the case in real practice. Other studies impose simple rules in station choice, such as selecting the nearest station or charging at home (Dong et al., 2017; Ke et al., 2019). These assumptions are also overly restrictive because charging decisions are largely influenced by aggregate charging demand and battery constraints, e.g., the nearest station may be too crowded, and the battery may not be sufficient for a trip back home.

On the other hand, data-driven studies avoid making assumptions on charging preferences but directly uncover them from real charging events. While early studies rely on trip-level data that either cover a limited number of vehicles or include periods when the share of EVs was still limited (Fraile-Ardanuy et al.,

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2018; G. Wang et al., 2020), recent research on the fully electrified taxi fleet in Shenzhen provided deeper insights into the spatiotemporal charging pattern and station choice preference among a large number of EVs (e.g., Lei et al., 2022; Guo et al., 2022). Several studies also estimate the charging demand based on trip data but rely on assumptions that drivers always fully recharge or start charging at some predefined SOC threshold (G. Wang et al., 2023; Jin et al., 2025) However, as revealed in this study, taxi drivers may start charging from any SOC level and often perform partial charging. Furthermore, most previous studies identify charging events in the uninterrupted trajectory, whereas Lei et al. (2022) has revealed that the GPS devices are turned off when vehicles perform long-time charging. Consequently, a particular type of charging event has been largely overlooked in the literature.

In this study, we uncover and analyze the electric taxi charging behavior using the GPS trajectory of a fully electrified taxi fleet collected in Shenzhen, China, in 2020, together with citywide charging station information. We identify two types of charging events based on their locations: i) *opportunistic charging* at public charging stations, and ii) *dedicated charging* at commercial charging stations only accessible to taxis. In general, opportunistic charging is associated with much shorter charging times and concentrates in central urban areas, while dedicated charging serves the majority of charging demand and exhibits clear temporal peaks. We further proposed a method to estimate the queue time and actual charging duration, from which the SOC trajectory is constructed for each vehicle. The results reveal that taxis operate with SOC levels above 50% for most of the time, indicating a relatively conservative operational strategy. Finally, we extract POI information near charging stations and classify them into six clusters. The results show a clear preference for some station clusters during certain periods of the day. These findings thus provide valuable insights for charging infrastructure planning and battery design to improve infrastructure utilization and reduce system costs.

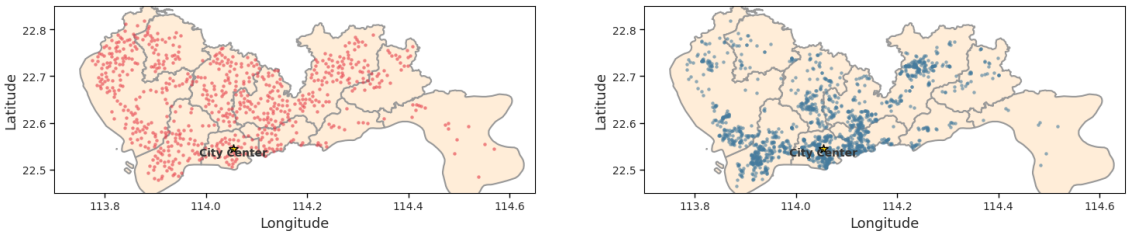
2 Data

Electric taxi trajectory data

Trajectory data used in this study includes the full electrified taxi fleet in Shenzhen over the period from January 1 to January 7, 2020. All taxis belong to the same model and are equipped with a battery of capacity 80 kWh (maximum driving range of 400 km) and maximum charging power 43 kW (G. Wang et al., 2021). Based on these specifications, we assume a fixed energy consumption rate of 0.2 kWh/km. Notably, this battery differs from assumptions adopted in some previous studies, which set the battery capacity of electric taxis in Shenzhen as 57 kWh (G. Wang et al., 2019; Lei et al., 2022). Since our analysis is limited to Shenzhen, we filter taxis with trajectories fully inside the city, which yields a fleet of 15,853 vehicles.

Charging station data

The charging network in Shenzhen consists of two types of charging stations: i) *commercial charging stations* that are dedicated to serving taxis, and ii) *public charging stations* that are accessible to both taxis and private vehicles. Commercial stations typically use high-power fast chargers to meet high charging demand, whereas public stations provide more flexible charging with relatively low-power chargers. We collected the data of 695 commercial charging stations from the open Baidu Map platform. Detailed information of public charging stations is taken from Li et al. (2025), which was collected in 2022. To make the charging station data consistent with the trajectory data from 2020, we identify and remove stations or charging piles installed after 2020. According to (Ou et al., 2020; Jin et al., 2025; Lei et al., 2022), by 2020, public chargers in China typically operated below 60 kW and commonly around 7 kW. Hence, we remove charging piles with power larger than 60kW and stations without a valid charging pile. This filtering results in 1,478 public charging stations illustrated in Figure 1, along with the commercial charging stations. Both types of charging stations are distributed in the western and central areas with higher population density and major economic activities. Differently, public stations are more concentrated in the city center and subcenters, while the commercial stations are more evenly distributed over the city as they typically require a larger space.



(a) commercial stations

(b) public stations

Figure 1: Charging stations distribution

3 Methodology

Charging activity identification

This section presents the method used to identify charging activities at the two types of charging stations, which serves as the basis for the subsequent analysis of charging behavior patterns.

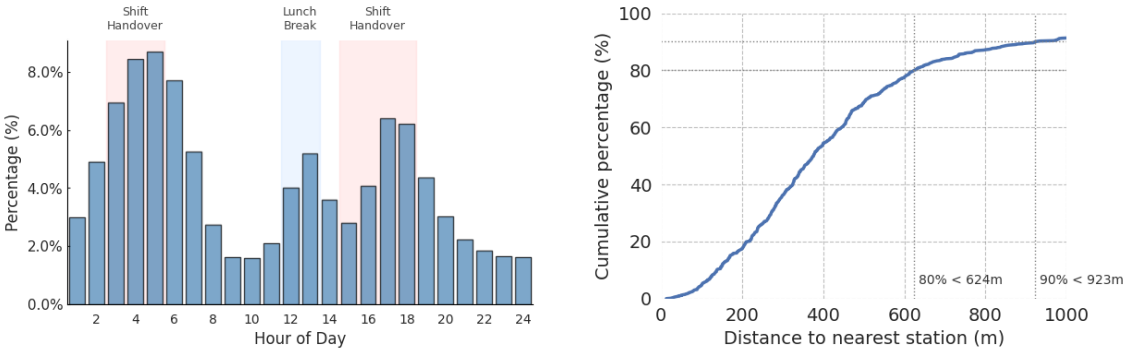
Public station charging

Public charging events are identified by matching taxi locations with charging station locations. Following previous studies (Lei et al., 2022; Guo et al., 2022), a vehicle is considered to have a potential charging event if it remains within a 200-meter radius of a station for at least ten minutes. Each event records the vehicle ID, station ID, arrival and departure times, and charging pile information (number and power). Note that this procedure just identifies episodes in which vehicles stay within the vicinity of a charging station, and therefore represents potential charging events. Whether actual charging occurs depends on queueing conditions at the station. This distinction from previous studies will be discussed further below.

Commercial station charging

Long interruptions in trajectory data may correspond to breaks, such as lunchtime, when drivers manually switch off the GPS device and recharge vehicles (Lei et al., 2022; G. Wang et al., 2019). In this study, we treat GPS interruptions longer than 30 minutes as intentional shutdowns and consider them as potential charging events at commercial stations. The 30-minute threshold is chosen for two reasons. First, charging during breaks or shift changes usually lasts longer, especially given the larger battery capacity of electric taxis, making 30 minutes a more reasonable minimum charging duration than the 10-minute threshold used in previous work (Lei et al., 2022). Second, this duration helps filter out brief signal losses caused by communication issues. Using this criterion, we identify 315,906 GPS interruption events. Each event records the vehicle ID, the last GPS location before the interruption, the first location after the interruption, and the duration of the data gap.

To further examine whether these interruptions correspond to charging at commercial stations, we conduct spatial clustering using DBSCAN based on the last reported GPS locations before interruption. The temporal and spatial characteristics of these clusters are presented in Figure 2. The time distribution shows clear peaks during early morning (3:00–5:00) and afternoon (15:00–18:00), which correspond to typical taxi shift-handover periods (Zhang & Tan, 2024), as well as around lunchtime when drivers usually take breaks. During these periods, drivers are likely to recharge at commercial stations to quickly refill and prepare for subsequent operations (Bauer et al., 2021). The distance CDF (Fig. 2b) further shows that these GPS interruptions generally occur close to commercial charging stations, supporting our assumption that such outages correspond to charging activities. To highlight the spatial characteristics more clearly, we select a 5km $\times$ 5km area with the highest concentration of GPS interruptions (Figure 3). The results show that these interruption points are predominantly located near commercial charging stations, with an average distance of less than 500 meters. Based on these observations, we label an interruption as a commercial charging event when its last GPS point is within 500 meters of a commercial station. This larger threshold, compared with the previously used 200-meter radius, accounts for the relatively long GPS reporting interval (typically 30–60 seconds), during which the vehicle may still move before the device is turned off.



(a) Time-of-day distribution

(b) Distance to nearest station (CDF)

Figure 2: Spatiotemporal characteristics of GPS interruptions

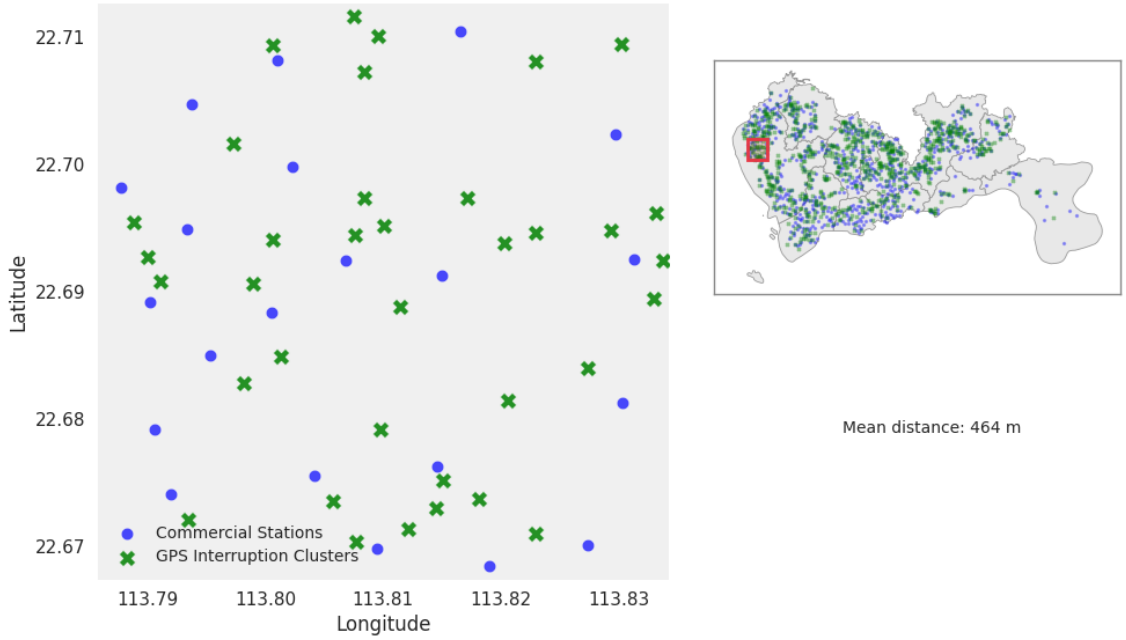


Figure 3: GPS interruption clusters

Queuing and charging time calculation

Queuing is assumed to be negligible at commercial charging stations due to their large capacities, whereas drivers at public stations with fewer piles may endure a considerable queuing time for charging. Although private EVs can also charge at public stations, their impact on taxi charging is almost negligible as previous studies indicate that private EVs are mostly charged at home (SHEVDC, 2017; Virta, 2022) due to the much lower electricity prices Tam et al. (2024). Therefore, in this study, we estimate the queuing time based on taxi arrivals, charging durations, and the number of piles. For each station, all charging events are first sorted in ascending order of arrival time. We assume that vehicles arriving earlier are served first. For a new vehicle that arrives at time t_a and departs at t_b, based on the observed dwell time of each vehicle, we can determine how many vehicles are still charging, as well as their departure times. This allows us to identify the earliest time when a charger becomes available, denoted by h^*. The queuing time is thus calculated as $w = \max\{0, h^* - t_a\}$. The newly arriving taxi can start charging immediately if $w = 0$. Otherwise, the vehicle has to wait for w, and the actual charging duration is $x = \max\{t_b - t_a - w\}$.

SOC trajectory

We assume all taxis start their operations with a full battery. Hence, the SOC trajectory can be constructed using the travel distance extracted from the GPS data and charging activities identified above. Specifically, we compute the charging amount based on the charging power and duration, and cap it with the battery capacity. The charging power is set to the maximum vehicle charging power (43 kW) for commercial stations

and computed as the average charging power for public stations. The energy consumption is computed based on the travel distance extracted from the GPS data and the per-kilometer energy consumption rate.

Station clustering

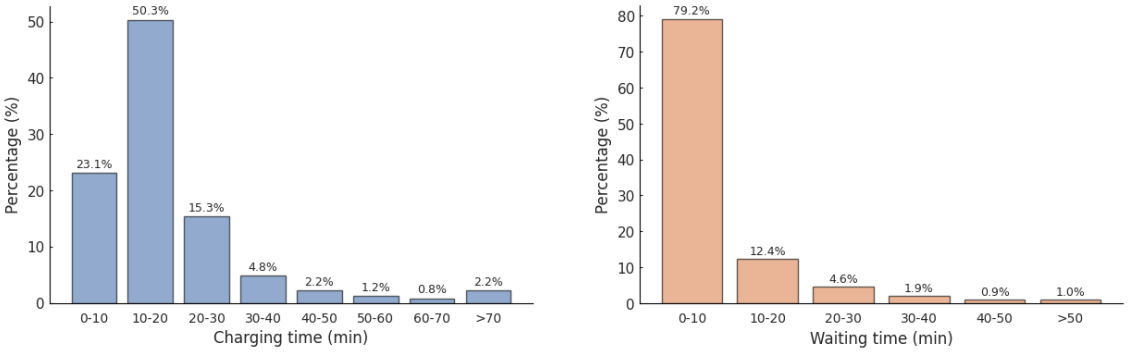
We collected the POI types and counts within 200m of each station and used the fractions of POI by type as features to classify stations via hierarchical clustering. We then compute the average number of charging events served by each cluster of stations across time periods to explore the preference for charging stations.

4 Results and discussion

Spatiotemporal charging patterns

Applying the above method, we identify 267,013 commercial charging events and 150,038 potential public charging events. On average, each taxi performs 2.41 commercial charges and 1.19 public charges per day. The overall charging frequency is 1.77 charges per taxi per day, close to the value of 1.7 reported in previous studies (e.g., Lei et al., 2022) In addition, approximately 7.8% of public charging attempts are abandoned due to extensive long waits.

Figure 4 plots the distributions of charging and queuing times at public stations. In sum, around 80% of vehicles wait less than 10 minutes, while fewer than 10% of charging events involve waiting times exceeding 20 minutes. Besides, over 95% of charging sessions terminate within one hour, with about half lasting only 10–20 minutes. Given that most chargers at these stations have power ratings below 10 kW, these results indicate the prevalence of partial charging, which will be discussed in detail later.



(a) charging time

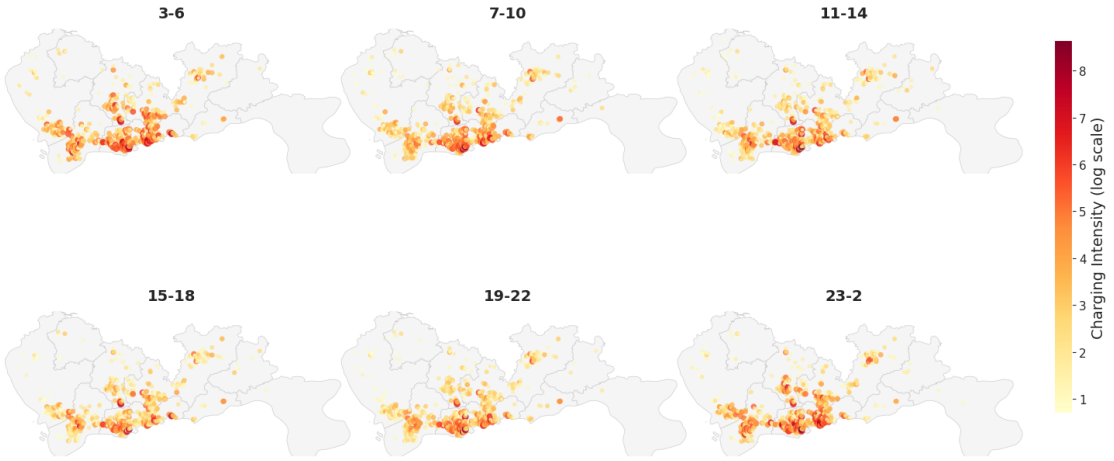
(b) queuing time

Figure 4: Charging and queueing time at public stations

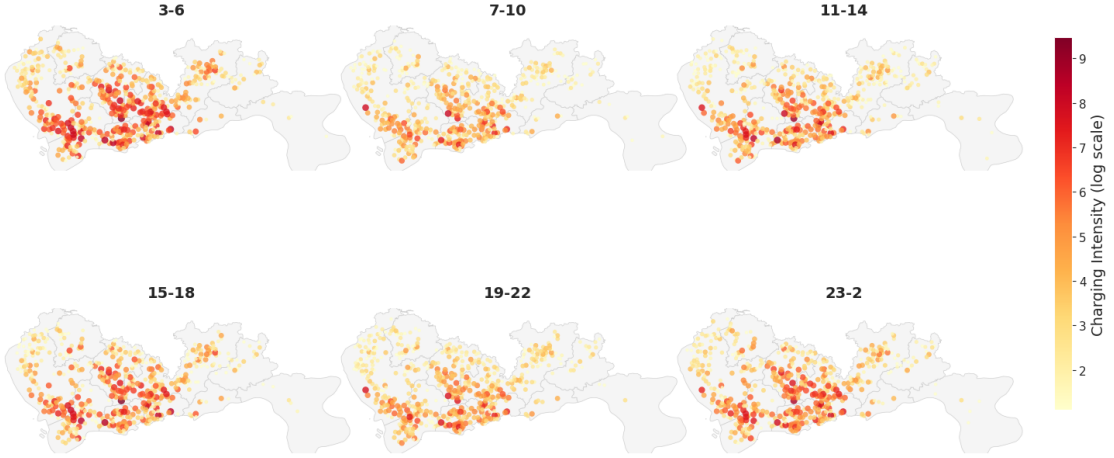
To analyze the spatiotemporal characteristics of charging at the two types of stations, we divide the day into six time periods: 03:00–06:00, 07:00–10:00, 11:00–14:00, 15:00–18:00, 19:00–22:00, and 23:00–02:00. For each period, we calculated the average daily number of charging events per station, which is illustrated in Figure 5 in logarithmic scale. It can be observed that commercial charging exhibits more pronounced spatiotemporal variation. Temporally, more charging events are observed during taxi shift handovers (03:00–06:00 and 15:00–18:00), consistent with earlier findings. Spatially, most commercial stations are used, though stations farther to the north are less visited. During the taxi shift handover periods, a hot spot in the southwest can be easily recognized, where the number of charging events drops significantly in other periods. In comparison, public charging occurs less frequently than commercial charging throughout the day and is more concentrated in the city center and subcenters, where passenger demand is relatively high. Temporal variation in public charging is less evident, suggesting that these charging decisions are highly opportunistic and random.

SOC trajectory analysis

Based on the estimated SOC trajectory, Figure 6 reports the proportion of taxi operation time with certain SOC levels over the study week. Throughout the week, taxis operate at a SOC above 50% for almost 85% of the time, while they rarely operate with an SOC below 20%. These results suggest that taxi drivers are



(a) Public charging



(b) Commercial charging

Figure 5: Spatiotemporal features of charging activities

quite conservative and tend to keep the vehicle battery half full to react to unexpected situations. This result, however, indicates potential inefficiency in the charging network design and resource allocation.

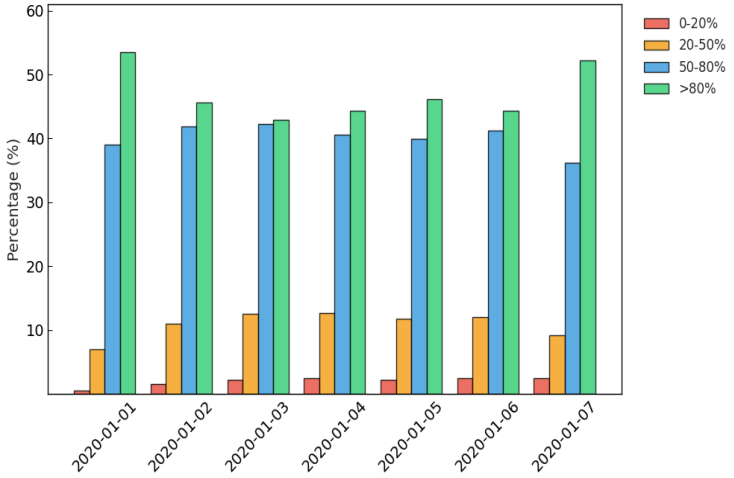


Figure 6: Distribution of vehicles in different SOC range.

Figure 7 shows the distribution of vehicles across SOC levels at different times of the day (averaged over seven days). The temporal pattern is consistent with the charging and routing behavior. Following the commercial charging peaks at 04:00–06:00 and 17:00–18:00, the share of high-SOC vehicles (90%–100%) increases significantly after 06:00 and 18:00, while the proportion of very low-SOC vehicles (below 20%) diminishes. From 07:00 to 16:00, vehicles are mainly engaged in service, leading to a gradual increase in the share of vehicles with medium-to-low SOC. Around midday, some drivers temporarily recharge their vehicles, resulting in a modest rise in the proportion of vehicles with SOC between 80% and 90%. Although SOC levels between 20% and 50% are still observed, such cases occur almost exclusively during the early morning when passenger demand is low.

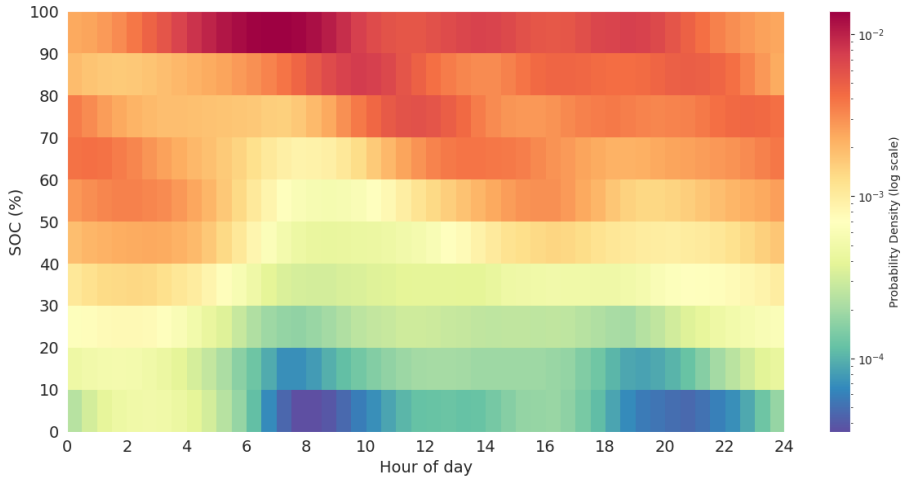


Figure 7: Distribution of vehicles across SOC and hour of day

To better illustrate partial charging, Figure 8 plots vehicle SOC before and after charging. While partial charging is observed in both commercial and public charging, the energy charged at public stations is noticeably smaller than that at commercial stations, suggesting that drivers primarily replenish energy at commercial stations.

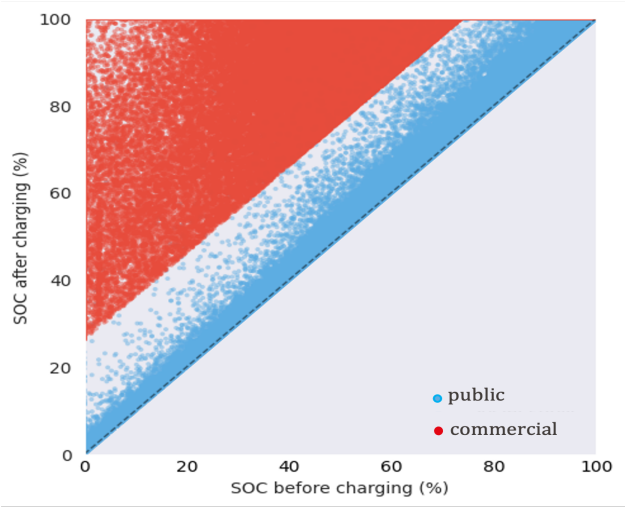
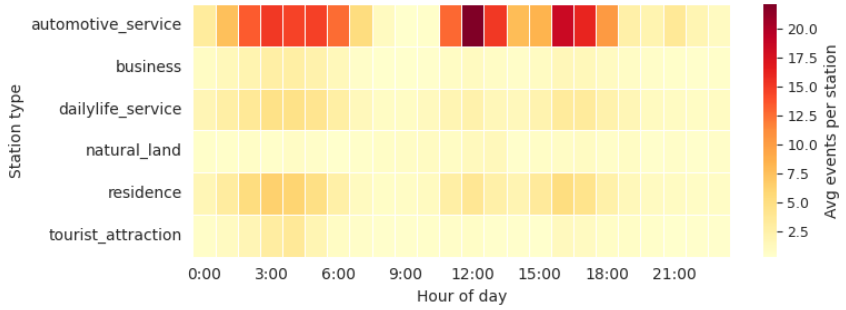


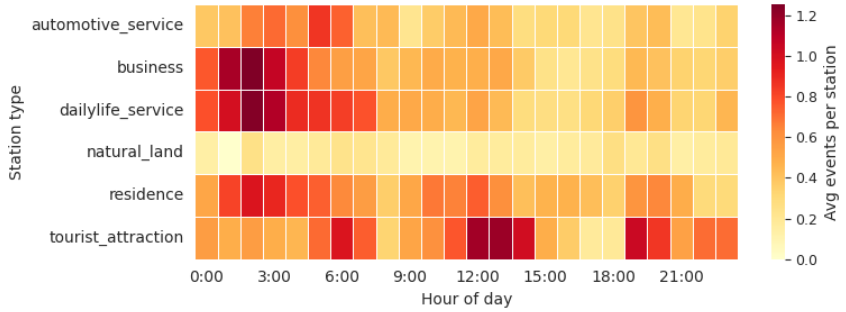
Figure 8: SOC before and after charging

Station classification and influence on charging behavior

Using the POI information, both commercial and public stations are classified into six categories. Each category is dominated by a single POI type accounting for more than 60%, thus is named accordingly: *automotive_service, business, dailylife_service, natural_land, residence, and tourist_attraction*.
Figure 9 shows the average number of charging events served per category across different periods. For commercial stations, drivers show a clear preference for stations close to *automotive_service* POIs, with charging demand concentrated during several peak periods throughout the day. As for public stations, preferences are observed for those close to *business* and *dailylife_service* POIs over night and those close to *tourist_attraction* POIs at noon and in the evening.



(a) commercial station charging



(b) public station charging

Figure 9: Temporal average charging event across POI-based station types

5 Conclusions

This study analyzes taxi charging behavior in Shenzhen using the trajectory of a full electrified taxi fleet and citywide charging station data. Distinct spatiotemporal patterns of charging behaviors are revealed at two major types of charging stations: commercial stations dedicated to taxis and public stations also accessible to private vehicles. While both commercial and public charging concentrate in the city center, commercial charging exhibits clear peaks during the taxi shift handovers. In contrast, public charging shows less temporal variation, implying an opportunistic nature. Two noticeable findings from the SOC trajectory analysis are that vehicles operate mostly above 50% SOC and partial charging is common, particularly in public charging events, suggesting that current battery capacity exceeds operational needs. Finally, the POI-based station classification indicates diverse preferences for the two types of charging stations over different periods of the day.

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