

Understanding Operational and Charging Patterns of Electric Vehicle Taxis Using GPS Records

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Abstract—The major obstacle to the wide acceptance of Electric Vehicles (EV) is the lack of a wide spread charging infrastructure. To solve this, the Chinese government has promoted EVs in public transportation. The operational patterns of EV taxis should be different from Internal Combustion Engine Vehicles (ICEV) taxis: EVs can only travel a limited distance due to the limited capacity of the batteries and an EV taxi may re-charge several times throughout a day. Understanding the status (e.g., operational patterns, driver income and charging behaviours) of EV taxis can provide invaluable information to policy makers. To our best knowledge, this is the first paper to understand EV taxi behavior patterns. We use real taxi GPS records data from a fleet with about 600 EV taxis operating in Shenzhen, China. We study the patterns from two aspects: operational behaviors and charging behaviors. The most important finding is: based on the net profits of both EV and ICEV taxis, which are derived from data, we find that commercial operation of an EV taxi fleet can be profitable in metropolitan area, when specific policies give advantages to EV taxis.

I. INTRODUCTION

Electric Vehicles (EV) are more and more popular, due to the strengthen public willingness of contributing to environment protection. Compared with Internal Combustion Engine Vehicles (ICEV), EVs have zero air pollution.

The major obstacle to the wide acceptance of EV, nowadays, is the lack of a wide spread charging infrastructure. Unlike ICEVs' convenience of rapid refueling at gas stations, EVs need to re-charge via charge piles. EV infrastructure mainly refers to a network of charge stations where EVs can be charged. There is a closed loop: the negligible number of EVs is the major reason of the lack of infrastructures; due to the lack of infrastructures, people are reluctant to buy new EVs, which in turn limits the increase of the number of EVs.

One effort to break the loop, from the government, is to use EVs in public transportation, more specifically, taxis and buses. In 2009, the Chinese government picked 13 cities (including Shenzhen, Beijing and Hangzhou) to launch EV public transportation. Among them, Shenzhen has the most successful EV taxis service: it starts to make profit in 2013.

The operational patterns of EV taxis should be different from ICEV taxis. Compared with an ICEV taxi, an EV taxi can only travel a limited distance per charging due to the limited capacity of its battery. As a consequence, an EV taxi may re-charge several times throughout a day. What's more, each charging event usually costs much longer time

compared with an ICEV refueling event: every recharging lasts for more than one hour, even with the fast charging mode.

Understanding the operational patterns of EV taxis can provide invaluable information to policy makers. For example: would these features, including battery capacity and recharging duration, significantly affect the operational distance/time/income of taxis? Does EV charging behaviors follow any patterns? The answers to such questions can help planning of new charge stations, expanding of existing stations, and estimating the business potential of new EV taxi fleets.

To our best knowledge, this is the first paper to understand EV taxis' behavior patterns. We use real taxi GPS records data from a fleet with about 600 EV taxis operating in Shenzhen, China. We study the patterns from two aspects: operational behaviors and charging behaviors. The main contributions of this paper include:

- Overall, the travel and occupied time/distance are comparable between EV and ICEV taxis. We derive the net profits of both EV and ICEV taxis, and find that an EV taxi can earn almost as much as an ICEV taxi although the EV taxi spend more time on charging. The implication is that commercial operation of an EV taxi fleet can be profitable in metropolitan area, when specific policies give advantages to EV taxis.
- The distribution of charge demands have direct relationship with the number of charging piles of every charge station. We also find that a particular charge station can be under-utilized if it's far away from other charge stations. The implication is that location planning of charging stations might need to consider the distance among stations.
- We find that although EV taxi companies declare the maximum trip distance per full-charging of an EV taxi is 240 Km, the actual trip distance between two consecutive charge events of most EV taxis is only about 110 Km. The implication are two fold: battery capacity decreases significantly over time, leading more charging times and less travel distance; distance limitation enforced by battery capacity affects drivers' charging behaviours.

This rest of the paper is organized as follows. In Sec-

tion II, we describe the data sets and analyze methodologies. Section III investigates the collective operational behavior patterns of EV taxis and compare it with ICEV taxis. In Section IV, the collective charging behavior patterns of EV taxis are explored. The related works are discussed in Section V. We conclude the paper in Section VI.

II. STUDING CASE

A. Overview of Electric Taxi in Shenzhen

The studying case used to understand EV taxis' behavior patterns is in Shenzhen, China. The amount of EV taxis is around 1000 until 2014. Considering the total amount of taxi fleets in Shenzhen, the percentage of EV taxis is less than 10%. Due to the limitation of battery capacity, EV taxis can only travel a certain distance compared with ICEV. A number of charging stations have been built and deployed in Shenzhen, offering fast charging piles for EV taxis.

We list and compare different EVs used for taxis in different cities in Table I. BYD e6 is adopted in Shenzhen. Compared to other types of EV taxis, BYD e6 can travel more distance and faster.

TABLE I
EV TAXIS IN CITIES

City	Shenzhen	Beijing	Hangzhou
Vehicle Type	BYD e6	CHANGAN E30	HAIMA PULIMA
Nominal Maximum Distance per full-charging	240 Km	160 Km	80 Km
Maximum Speed	160 Km/h	120 Km/h	70 Km/h
Battery Capacity	72 kWh	29 kWh	24 kWh
Full-charging Time	60 minutes	45 minutes	30 minutes

Our field analysis indicates that passengers in Shenzhen prefer to take EV than ICEV taxis. There are two main reasons. First, to promote the usage of EV taxis, a law is carried out that: a passenger needs to pay additional 3 RMB per trip for an ICEV taxi, but not for a EV taxi. Second, BYD e6 is larger and more comfortable than standard ICEV vehicle types. The result is that EV taxis are easier to pick up passengers when compete with ICEV taxis. This user preference has critical effect on EV taxis' operational conditions, which we will demonstrate in later analysis.

B. Dataset Description

The major dataset is taxi GPS records. The dataset consists of over 14,000 taxis, including around 600 (out of 1000) EV taxis and around 13,000 ICEV taxis. Each taxi updates a GPS record per 30 seconds in average, together there are around 4 GB data per day and over 28 GB per week. We use the dataset from March 1st, 2014 to March 7st,2014, lasting for one week.

The taxi GPS records data description is showed in Table II. The longitude and latitude fields together present the spatial position of a taxi; the time field gives the time of a specific taxi report. The CarType and Company fields tell us whether a taxi is an EV. Note that there are also two types of ICEV: red for urban areas and green for suburb areas. Since

TABLE II
TAXI GPS RECORD

CarId	Unique identity for a taxicab
CarType	For EV,it's blue;for ICEV,it's red and green
Company	name of company one taxi belongs to
longitude	longitude of location recorded
latitude	latitude of location recorded
time	time of recorded: 2014-03-01T04:52:15.000Z

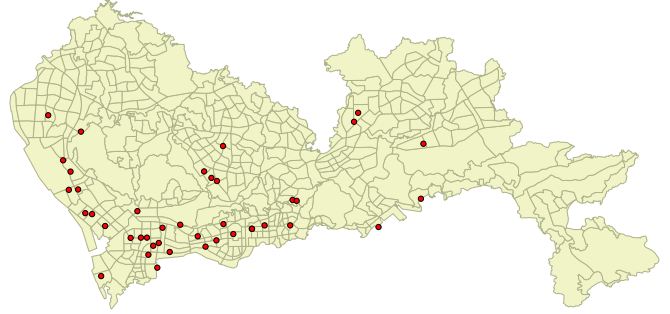


Fig. 1. Distribution of charge stations in Shenzhen

green taxis only operate in the suburb areas of Shenzhen City and their charging mode is also different from red and blue taxis, we omit those green taxis and only choose red taxis as representatives of ICEV taxis.

Another dataset is taxi transaction records. The data fields description are given in Table III. Combined the information from GPS and transaction, we can derive the information of where a taxi picks up and drops off a passenger (*i.e.*, the OD-pair data). The distance field can be used to calculate taxis' operating distance precisely and the field of fee can be used for calculating taxis' income.

TABLE III
TAXI TRANSACTION RECORD

CarId	Unique identity for a taxicab
uptime	time of a taxi picking up a passenger
downtime	time of a taxi dropping off a passenger
distance	distance of operating a trip
fee	fee of a trip (not including additional ICEV fee)

GIS data is used to describe Shenzhen City and the distribution of every charge station in Shenzhen as shown in Figure 1. Every red dot refers to the location of one charge station and the background zones refer to Shenzhen City.

C. Analyze methodology

Charge event detection We need to extract charge events. The observation is that a charge event always lasts for a long time; as a consequence, the longitude and latitude values of every GPS record are nearly constant during this period. Using this feature, we can detect charge events from large amount of GPS records, as shown in Figure 2.

We use the location of every charge station as the center and a distance of 200 meters as the radius to obtain a circle region called stay region. Every dot refers to a GPS record

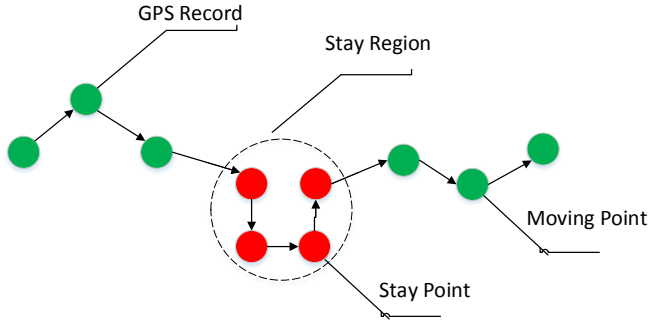


Fig. 2. Charging Event Detection

tagging both spatial and temporal information. When an EV taxi reaches a charge station, many GPS records drop into the stay region. We use 30 minutes as a time threshold value, meaning the time interval between the first and the last GPS records located in a stay region should be larger than the time threshold. After obtaining a stay point set, we use the information of first and last GPS records to learn when an EV taxi reaches and leaves a charge station and how long the charge event lasts.

Ground truth To evaluate whether the charge event detection methodology works well in reality, we chose one charge station on which to perform a field study. This field study lasted from 4:00pm to 6:30pm on July.20, 2014. We recorded the EV taxis' arrival and departure time, and also how long each EV taxi spent on charging. Totally, 30 charging records were collected as a ground truth to evaluate the charge event detection methodology.

Using our methodology, we obtain EV taxis' charge events on that charge station at the period. We compared the filtered results with the ground truth: for totally 30 EV taxis from the ground truth, 29 EV taxis' charge events could be correctly detected, meaning the accuracy of our charge event detection is about 96.7%.

Coverage and distance For each taxi, we sort all its records in time sequence and obtain a trajectory of the taxi like this: $R_1 \rightarrow R_2 \rightarrow \dots \rightarrow R_n$. The centroid of a specific taxi K can be calculated by Equation 1:

$$centroid_K = \left(\frac{\sum_{i=1}^n R_i.lon}{n}, \frac{\sum_{i=1}^n R_i.lat}{n} \right). \quad (1)$$

For analyzing taxis' coverage, we use the centroid and radius of gyration. The gyration radius of a taxi K can be calculated by Equation 2; we also define $dist(R_i, centroid)$ to represent its distance from this taxi's centroid.

$$radius_K = \frac{\sum_{i=1}^n dist(R_i, centroid)}{n} \quad (2)$$

With consecutive GPS records of taxi K, we define $dist(R_t, R_{t+1})$ to represent the distance between those two GPS records so we can calculate the total travel distance of taxi K by Equation 3:

$$SumDist = \sum_{t=1}^n dist(R_t, R_{t+1}). \quad (3)$$

III. OPERATIONAL BEHAVIORS

EV taxis' behavior patterns consist of two parts: operational and charging. We first analyze both temporal and spatial operational patterns and highlight how these patterns are different from those of ICEV taxis.

A. Temporal Operational Characteristics

The results of both EV and ICEV taxis' temporal operational patterns are shown in Figure 3. In China, many taxis operate for a whole day by time-division-multiplexing between two drivers. Figure 3(a) shows the distributions of total travel hours. About 30% of ICEV taxis travel less than 8 hours; it is obvious that they are operated by a single driver. Compared with ICEV taxis, almost all EV taxis work for longer than 19 hours; take the time spending on charging into consideration, we can safely assume that almost all EV taxis work for a whole day. For fair comparison, we filter the results of those ICEV taxis which only work for a half day in the rest of the paper.

After filtering, we compare occupied time (the taximeter is on) between EV and ICEV taxis in Figure 3(b). The distributions of occupied time between EV and ICEV are comparable: most taxis have around 9~10 hours with taximeter on. From Figure 3(a) and (b) together, we can observe that ICEV taxis' average length of both operating and occupied time are longer than that of EV taxis. The implication is that: *charging demand do have large negative effects on EV taxis' operational time.*

Figure 3(c) shows the distribution of the ratio between occupied time and total time. About 73% of ICEV taxis' ratio value is 0.4~0.5; while 85% of EV taxis' ratio values fall in this range. An EV taxi efficiency of operating is higher than that of an ICEV taxi: although EV taxis lost much time on charging, their time of seeking a passenger is much less than ICEV taxis. The implication is that: *the additional fee law and the comfortability do have large positive effects on passengers' favour of EV taxis.*

B. Operational Distance

From taxi GPS record data, taxis' average travel distances per day can be calculated. The operating distance distribution of EV and ICEV taxis are showed in Figure 4(a). Most EV and ICEV taxis travel in a range of 450 Km~550 Km. ICEV taxis' proportion of over 500 Km is larger than that of EV taxis.

From taxi transaction data, we can obtain occupied distances. Figure 4(b) shows the distributions of occupied distances comparison. The majorities of both locate in a range of 250 Km~350 Km. The proportion of EV taxis dropping in this range is a little higher compared with that of ICEV taxis. Figure 4(c) shows the distribution of ratio between occupied distance and total distance; EV taxis efficiency of operating is higher than ICEV taxis. The analysis in distance verified our temporal characteristics obtained above.

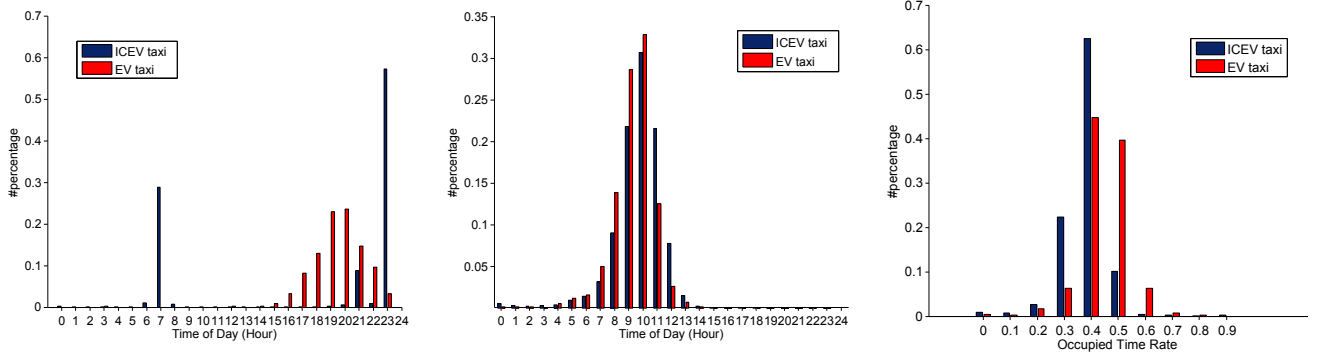


Fig. 3. (a) Total hour compare (b) occupied hour compare (c) ratio of occupy/total compare

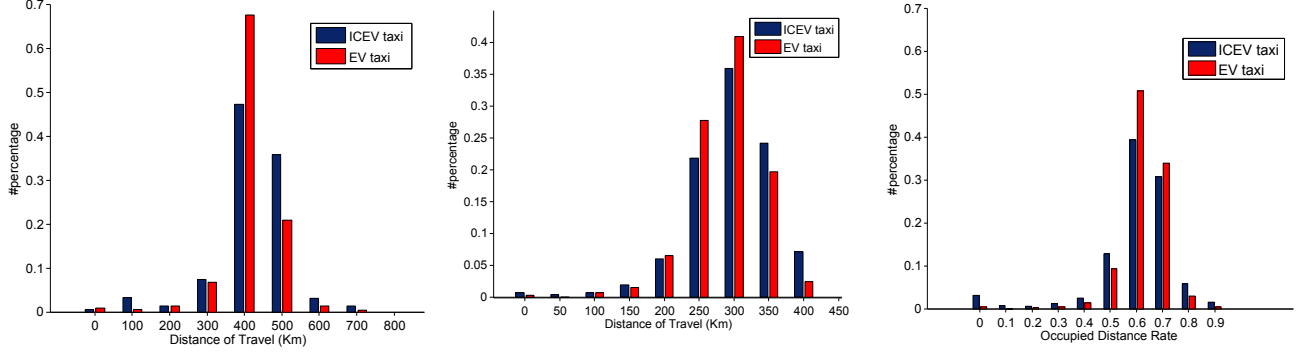


Fig. 4. (a) Total distance compare (b) occupied distance compare (c) ratio of occupy/total compare

C. Operational Coverage

Centroid and gyration radius can demonstrate a taxi's operating coverage. By analyzing the moving trajectories, we get the centroid and gyration radius of each taxi. For EV taxis, we only consider moving trips; those records of extracted charging events are filtered before calculation.

Figure 5(a) and (b) show EV/ICEV taxis' centroid distribution respectively. The deeper a zone's color is, the more centroids locate in the zone. We can observe that EV taxis' centroid frequency range value changes much sharper than that of ICEV taxis: the distribution of ICEV taxis' centroids is much more even than that of EV taxis. Further investigation shows that EV taxis' centroids are mainly distributed in those zones where a large number of charging piles exist.

The value of gyration radius can be used for further analyse. We find that EV taxis' radius of gyration is about 6.70 Km while ICEV taxis' radius is about 7.37 Km. Bigger radius value means that ICEV taxis can cover a larger areas than EV taxis. Investigations show that ICEV taxi drivers don't worry about re-fueling opportunities as much as EV drivers' about charging opportunities. By analyzing centroids and radius of gyration together, the implication is that: *EV taxi drivers prefer to operate around the locations of charge stations.*

D. Net profit comparison

In this part, we compare the net profit of ICEV and EV taxis. The related parameters are shown in Table IV. Both

taxis operate in the same mode: 10 RMB within 2 Km, and 2.4 RMB per Km after that. Actually, although passengers are more likely to choose EV taxis since they don't need to pay additional fuel fee, the number of average trips per day of ICEVs is still larger than EVs. As mentioned above, this is due to the reduction in EV operational time. Renting fee per day refers to the money that taxi drivers should give to their companies for the vehicles. The difference between oil price and electricity price is EV taxis' biggest advantage in cost: an ICEV taxi consumes 9.0 litres oil while a EV taxi requires 26 kWh electricity per 100 Kilometers.

TABLE IV
TAXI FEE COMPARISON (PER DAY)

	ICEV taxi	EV taxi
Operational Trips Count	48.00	44.00
Average Distances Per Trip(Km)	6.788	6.843
Income (RMB)	1223	1156
Renting Fee Per Day(Yuan)	200	360
oil price / electricity price	8.0	0.66
fuel consuming per 100 Km	9.0L	26kWh

Note that ICEV taxis can charge for additional 3 RMB per trip. An ICEV taxi drivers can obtain an additional 144 RMB per day. On the other hand, to promote EV usgae, EV taxi drivers could get 2000 RMB base salary from taxi companies, meaning 66.67 Yuan per day. All this factors need to be taken into consideration in net profit calculation.

For EV taxi drivers, we calculate their net profits using

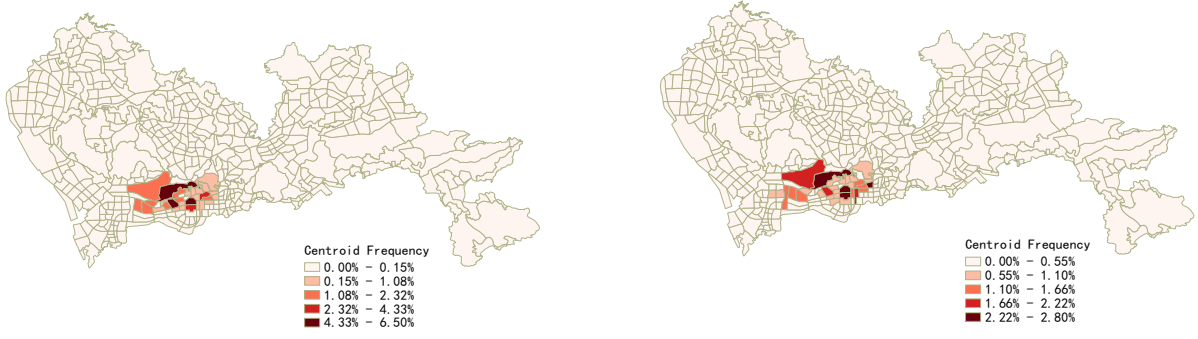


Fig. 5. (a) EV operating coverage (b) ICEV operating coverage

Equation 4:

$$EV\_Profit = \sum_{i=1}^n e_i - P_e \cdot S_e - R_e + B_e. \quad (4)$$

Here i refers to the i -th trip. Therefore, e_i means the money that earned by this operational trip. R_e is the renting fee; P_e is the electricity price per kWh and S_e is the total number of kWh of this EV taxi. B_e is the additional base salary from taxi companies.

For ICEV taxi drivers, we calculate their net profits using Equation 5:

$$ICEV\_Profit = \sum_{i=1}^n e'_i + P_a \cdot n - P_g \cdot D - R'_e. \quad (5)$$

Here i refers to the i th trip; e'_i means the money earned by this operational trip; R'_e is the renting fee; P_a is the additional fuel fee and n is the total number of operational trips; P_g is the gasoline price per kilometer and D is the total distance that this ICEV taxi traveled.

The results of net profits are as follows: an EV taxi can earn 535 RMB net profit per day on average, while an ICEV can earn 580.0 RMB. The results demonstrate that the difference between petroleum price and electricity price is EV taxis' biggest advantage in operating. The implication is that *the additional fee is a rapier: it does increase the trips per day for EVs, but also reduces the net profits.*

To sum up, we prove that commercial operation of an EV taxi fleet can be profitable in metropolitan area.

IV. CHARGING BEHAVIORS

A. Charging Demand Distribution

For every charge station, we accumulate the number of charging events; the distribution of charging demand is shown in Figure 6(a). A dot in the figure refers to a charge station. The deeper the color is, the more charge demands the station receives. It is obvious that the distribution of EV taxis' charge demands is uneven, EV taxi drivers are inclined to choose some charge stations compared with others.

We list top-7 mostly used stations, together with their numbers of piles, in Table V. FuTian station has 116 charge

TABLE V
TOP-7 CHARGE STATIONS

Name of charge station	Number of charging piles	Charge demands per day
FuTian	116	1022
Taoyuan Cun	12	149
TianBei	16	129
Tiyu Guan	16	98
NanShan	16	73
Mingzhi Square	23	67
Xiangmi Lake	12	61

piles, which is much more than other charge stations; its daily charge demands is 1022, accounting for over 50% of the total charge demands. Other stations each has piles ranging from 12 to 23; the changing demands are comparable. The implication is that: *the number of charging piles is a major factor of station preference.*

Note that most charge stations have similar number (10 to 30) of charge piles but their usage frequency are different. For example, TianBei (16 charge piles) has 129 charge demands while Information College (20 charge piles) has only 2 charge demands per day; there are other factors influencing the distribution of charge demands. We cluster charge stations into three categories depending on their frequency of charge demands as Figure 6(b). The charge stations in zone A refer to those which frequency of charge demands is below 5, the charge stations in zone B refer to those which frequency of charge demands is over 50 while the charge stations in zone C refer to those which frequency of charge demands is about 20. The top-7 charge stations are clustered into zone B, meaning that when FuTian Charge Station has no available charge piles, EV taxi drivers are inclined to charge in other charge stations which is near FuTian Charge Station. We can also observe that since there are some charge stations distributed between zone B and zone C, leading to some charge demands happening in zone C.

Contrary to that, there are rarely charge demands emerging in zone A since between zone A and zone B no charge station

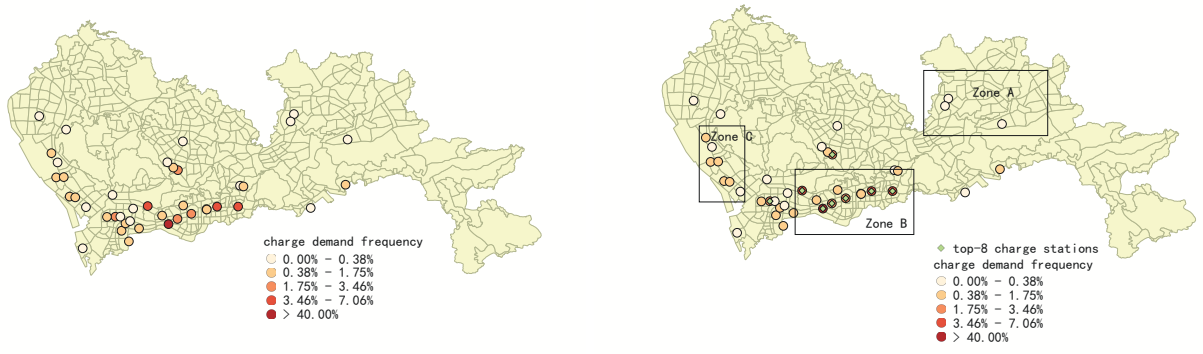


Fig. 6. (a) Charging Demand Distribution (b) Charging Location Distribution

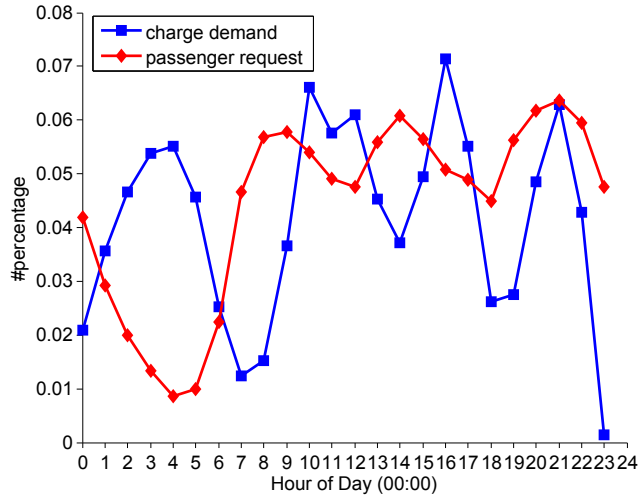


Fig. 7. Charging Temporal Distribution

is distributed, meaning that EV taxi drivers are afraid of using up battery energy and no charge stations for charging on the way. The implication is that: *the distribution of charge demands is also affected by relative locations of charge stations*. It is significant for deployment of charge stations, i.e., when deploy a new charge station, the distance between itself and other charge stations should be considered, avoiding the phenomenon of under-utilized charge stations in zone A.

B. Charging temporal distribution

Figure 7 shows the temporal distribution of charge demands. We also present the temporal distribution of passenger requests; note that these requests are gathered from both EV and ICEV taxis' transaction records. The implication is that: *temporal charging behavior is mostly affected by passenger requests*. When charge demands form a peak, passenger requests correspond to a valley and vice versa. It is obvious that EV taxi drivers always choose time of less passenger requests to charge their taxis; it is a reasonable choice which helps minimizing the lost during charging

hours. Figure 7 shows there are 4 peak periods for charging; we explain the details obtained from field investigation in Table VI.

TABLE VI
WORK TIME DISTRIBUTION

Work shift	Distribution of time	Charging time (Hour)	remark
Day shift	10:30 - 12:00	1.0	Having lunch and charge
Day shift	16:00 - 17:30	1.5	Full charge before shifting
Night shift	20:30 - 22:00	1.0	Having dinner and charge
Night shift	04:00 - 05:30	1.5	Full charge before shifting

C. Distance Before Last Hop

The concept of DBLH (Distance Between Last Hop) means the distance between the charge location EV taxis charging and the location of EV taxis last dropping off passengers before charging. In this research we calculate the frequency for different values of DBLH. The result is shown in Figure 8.

Figure 8 shows that most EV taxis' values of DBLH is less than 6 Km and about 42% of EV taxis' DBLH values are less than 2 Km; only a very small proportion of EV taxis' DBLH values is more than 10 Km. We use an exponential function for fitting this pattern and the equation is shown in Equation 6:

$$y(x) = 0.7567e^{-0.2683x}. \quad (6)$$

The implication is that: *EV taxi drivers always like to receive last passengers' requests whose destination is near charge stations*.

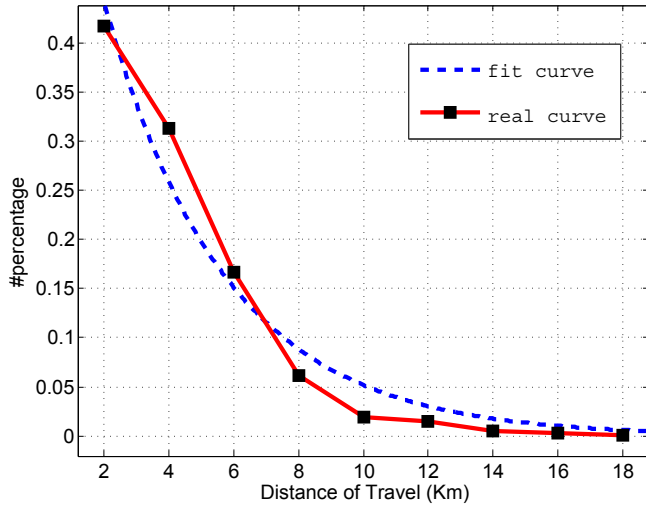


Fig. 8. Last Hop Distribution

D. Distance between consecutive charging events

According to the charging event records filtering from EV taxis' GPS records data, we could calculate total distance and occupied distance between consecutive charging events respectively, which will help us understand EV taxi drivers' charging behaviors better. The results are shown in Figure 9.

Figure 9(a) shows that most of EV taxi drivers travel about 106 Kilometers between consecutive charging events and Figure 9(b) indicates that most of EV taxi drivers operate a distance of about 65 Kilometers between consecutive charging events. Although EV taxi companies declare the maximum trip distance per full-charging of an EV taxi is 240 Km, the actual trip distance between two consecutive charging events of most EV taxis is about 106 Km.

There are two implications. First of all, *since fast charging mode is used for EV taxis to reduce charging time, it may weaken the battery capacity, leading to less distance that an EV can travel.* Secondly, *EV taxi drivers are afraid of battery using up, so they usually travel to charge stations for charging before the battery drops to a low state.*

For exploring battery attenuation problems further, we analyze every EV taxi's charging times per day and find that most of EV taxis would be charging 3~4 times throughout a day. Based on their charging times, we cluster EV taxis into two categories, i.e., one kind is to charge 3 times per day while the other kind is to charge 4 times per day. For those two categories, we calculate their distance between two consecutive charging events respectively and the results are shown in Figure 10.

We use cumulative density function (CDF) to analyze their distribution of distance between two consecutive charging events and it's clear that those charging 3 times per day can travel more distance than those charging 4 times. Actually, the main difference between them is their time when those EV taxis are put into market. Most of those charging 3 times per day are put into market for operating since December, 2012 while August, 2011 for those charging 4 times

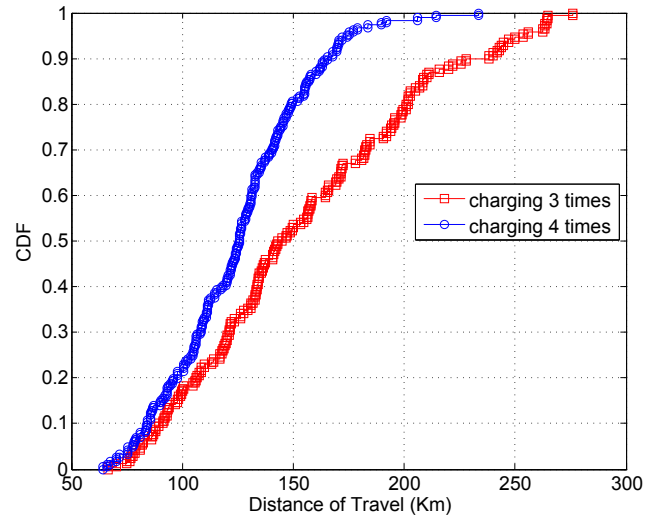


Fig. 10. Empirical CDF Distribution

per day. The implication is that: *battery capacity decreases significantly over time, leading more charging times and less travel distance per full-charged.*

Figure 9(c) shows the distribution of occupied rate between consecutive charging events. Occupied rate refers to the ratio between occupied distance and total distance between consecutive charging events. We use a Gaussian function for fitting this pattern and the equation is shown in Equation 7:

$$y(x) = 0.2874e^{-\frac{(x-0.673)^2}{2(0.1325)^2}} \quad (7)$$

Equation 7 shows that occupied rate of EV taxi drivers densely locate on the value of 0.673 and there are still a lot of occupied rates less than 0.5, which means that there still exists space to improve occupied rate by some taxi scheduling methods.

V. RELATED WORK

In recent years, the promotion of EV and deployment of EV infrastructure have led to massive researches which can be divided into EV charging location problem and EV charging schedule problem. Two models are used in EV charging location problem: flow-based model and activity-based model. For example, Kuby et al. [1] proposes the Flow Refueling Location Model (FRLM) for alternative-fuel vehicles and Kim et al. [2], Capar et al. [3] extend raw FRLM by adding new features. Jung et al. [4] use activity-based model to analyze queue delay of charge stations and offer decision support for choosing locations of undeployed charge stations aiming for minimizing EV taxi drivers' queue time for charging. Besides, Gharbaoui et al. [5] use activity-based model finding that in urban areas public charge stations can be underutilized and location selecting of charge stations should be considered to reduce EV owners' range anxiety.

Compared to EV charging location problem, more factors should be considered into EV charging schedule problem.

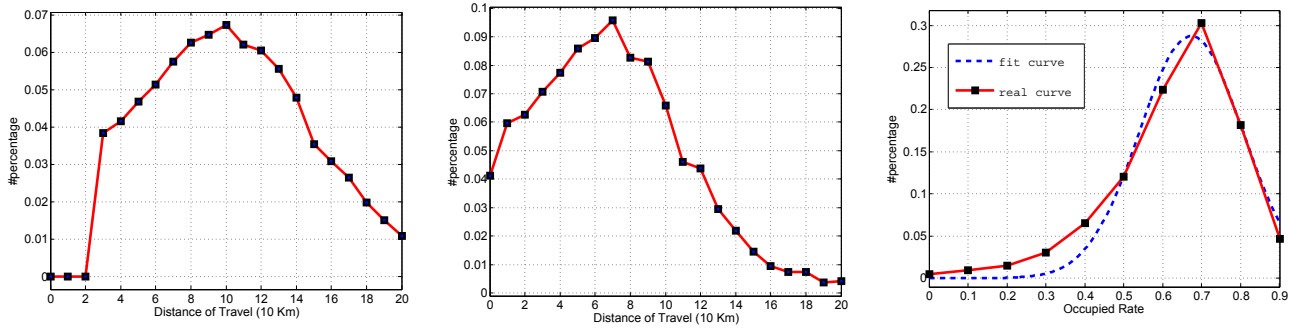


Fig. 9. (a) Total distance (b) occupied distance (c) ratio of occupy/total

For example, Ma et al. [6] and Gan et al. [7] use different decentralized charging control for reducing charging cost by avoiding charging during the electricity-used peak hours; Sundstrom et al. [8] propose a novel method to reduce the overloading in the power grid. Kim et al. [9] builds a reservation-based schedule system to respond to multiple charging request; Qin et al. [10] and Lu et al. [11] propose dispatching strategies for reducing EV charging waiting time so that EV taxi drivers can have more operation time.

VI. CONCLUSION

In this paper, we study the EV taxis' operational patterns from taxi GPS and transaction records in Shenzhen, China. To our best knowledge, this is the first paper to understand EV taxi behavior patterns. The most important finding is: based on the net profits of both EV and ICEV taxis, we find that commercial operation of an EV taxi fleet can be profitable in metropolitan area. There are also some implications need further investigation: the impact of distance among charge stations to drivers' decisions, the battery capacity may decrease over time, etc..

In the future, we would like to analyze EV taxi charging location problems, EV taxi charging schedule problems, and modeling the battery capacity decrease trend. We should consider how to choose locations of charge stations for reducing cost of EV taxi drivers. The cost includes distance traveling to charge station and time waiting for charging in some charge stations. We also plan to design related scheduling algorithms to schedule EV taxis' charge demands dynamically in order to reduce their waiting time for charging, which will promote the development of EV and EV infrastructures. At last, modeling the battery capacity decrease trend can help the administrator authority to run EV taxi fleet more efficiently.

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