Understanding battery degradation phenomenon in real-life electric vehicle use based on big data

Zhiyong Tian† Lai Tu† Yi Wang† Chen Tian§ Fan Zhang⋆
†Department of Electronics and Information, Huazhong University of Science and Technology, China
⋆Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, China
§State Key Laboratory for Novel Software Technology, Nanjing University, China
†{tianzhiyong, ywang, tulai}@hust.edu.cn, ⋆ zhangfan@siat.ac.cn, § tianchen@nju.edu.cn

Abstract— **As the rapid development of Electric Vehicles (EV), battery aging phenomenon becomes an emerging and challenging question to EV communities. However, battery degradation in real-life EV use has been discussed little. In this paper, by analyzing a large scale electric taxi GPS and deal data, we make the first attempt to investigate this problem. A case in Shenzhen is analyzed in this paper, where BYD e6 is used as the EV taxi type, offering us a real situation. Since data of battery management system (BMS) is not open in public, a new concept of travelled distance between two consecutive recharging events (TDC) is proposed to describe battery capacity loss. By utilizing historical TDC values of EV taxis, a statistic analysis method based on box-plot is proposed to understand battery aging. To evaluate battery performance and degradation in real-life EV use, we conduct experiments on nearly 4 years real EV taxi GPS data. The evaluation results demonstrate that external circumstances, such as temperature, road condition and charging rate, will have an impact on battery degradation in real-life EV use while the overall battery aging trend will be affected little.**

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 less air pollution.

Lithium-ion rechargeable batteries have experienced a rapid growth in EV utilizations, due to their high energy and power density. However, the overall performance of batteries is not constant along the vehicle life. As the use of EVs, their battery capacity will fade followed by the augmentation of internal resistance of batteries. This phenomenon of battery degradation can be commonly observed in EV industries.

Understanding battery degradation phenomenon is crucial for EV manufacturers to improve the performance of their battery management system (BMS), especially in real-life EV use conditions. Currently, most investigations and researches of battery aging mainly rely on simulated data and perform under controlled laboratory environment, which is not totally representation of a real EV use. Therefore, it's significant to explore battery degradation in real-life EV operation cycles.

However, exploring battery degradation in real-life EV use is not easy. Firstly, it's hard to have access to battery data since manufacturers' BMS information is not open to the public. Therefore, other suitable parameters of EVs should be selected to characterize battery aging. Secondly, life cycles of EV batteries always last for a long time, thus it needs a long-term tracking and recording of real-life EVs. Finally, it's difficult to model battery aging process due to the lack of battery capacity data, while the process is crucial for understanding battery degradation phenomenon.

In this study, we use real taxi GPS records data from a fleet with about 850 EV taxis operating in Shenzhen, China to explore battery degradation phenomenon. The main contributions of this paper include:

- Driving and recharging behavior patterns of EV taxi drivers have been analyzed based on big data. An amount of typical EV taxis are extracted as samples to explore battery degradation, while their recorded data during entire battery life is collected.
- Driving distance between two consecutive recharging events can be selected to characterize battery degradation phenomenon, as well as recharging frequency. Statistic analysis of historical driving distance gives an explanation of battery aging in real-life EV use.
- A descriptive curve of battery degradation based on driving distance and recharging frequency is proposed, similar to the result under laboratory environment. Besides, battery cycling times can also be calculated to be compared with the official data.

This rest of the paper is organized as follows. In Section II, the related works are discussed. Then in Section III, we describe the data sets and the type of EV analyzed in this paper. Section IV presents the methodology of exploring battery aging phenomenon based on our data sets. In Section V, we evaluate the experiments results. And finally, we conclude the paper in Section VI.

II. 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 a Flow Refueling Location Model (FRLM) for alternative-fuel vehicles and Kim et al. [2], Capar et al. [3] extend the raw FRLM by adding new features to solve the siting problem of charging stations by utilizing graph theory. 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. In [6], the FRLM has been extended by adding threshold coverage to solve the problem of location of fast charging stations in Orlando and the state of Florida.

Compared to EV charging location problem, more factors should be considered into EV charging schedule problem. For example, Ma et al. [7] and Gan et al. [8] use different decentralized charging control for reducing charging cost by avoiding charging during the electricity-used peak hours; Sundstrom et al. [9] propose a novel method to reduce the overloading in the power grid. Kim et al. [10] builds a reservation-based schedule system to respond to multiple charging request; Qin et al. [11] and Lu et al. [12] propose dispatching strategies for reducing EV charging waiting time so that EV taxi drivers can have more operation time. Sun et al. [13] explores how battery electric vehicle users choose where to fast-charge their vehicles from a set of charging stations, as well as the distance by which they are generally willing to detour for fast-charging.

Nowadays, battery aging phenomenon has been popular among industrial and academic communities. For example, Barre et al. [14] presented a summary of techniques, models and algorithms used for battery ageing estimation, going from a detailed electrochemical approach to statistical methods based on data. Jaguemont et al. [15] mainly analyze the impact of external temperature on battery capacity fade; Lam et al. [16] propose a battery aging model by integrating multiple impacting factors such as depth of discharge, charging rate and so on. While Hussein et al. [17] use artificial neural network based approach to estimate battery capacity fade in Li-ion batteries for EVs.

III. Studying Case

A. Electric Vehicle Type

The EV used to explore battery degradation phenomenon in this study is BYD e6 (Figure 1), adopted as EV taxis operating in Shenzhen, China. BYD e6 is equipped with a kind of $LiFePO_4$ battery and relative EV parameters can be observed in Table I.

TABLE I
PERFORMANCE PARAMETER OF BYD E6

Nominal Maximum Distance Per Full-charging	300Km
Nominal Maximum Speed	160 Km/h
Battery Capacity	60KWh
Power Consumption Per Hundred Kilometers	20KWh/100Km
Rated Voltage	3.3V

In this study, battery degradation refers to the reduction of battery capacity.

Fig. 1. The electric vehicle used in this study

B. Dataset Description

We analyze the GPS trace dataset of about 850 EV taxis in Shenzhen during the period 01/01/2013-10/31/2016, which includes the GPS records collected by EV taxis every 30 seconds (Table II) and the taxi transaction records during the same period (Table III).

TABLE II
TAXI GPS DATA DESCRIPTION

CarId	Unique ID of a taxicab
CarType	Flag indicating EV or ICEV
Company	Company which a taxi belongs to
Location	Longitude and latitude of the location
Time	Second-level timestamp (*e.g.,* 2014-07-01 04:52:15.000)
Occupied	Flag indicating meter on/off

The time span of the collected dataset is nearly 4 years, enough for us to understand battery aging phenomenon. By utilizing these GPS data, recharging events of EV taxis can be detected precisely. Detailed description of this recharging event detection can be observed in our previous study [18] [19].

TABLE III
TAXI TRANSACTION DATA DESCRIPTION

CarId	Unique ID of a taxicab
On/off time	Time when the taxis pick up/drop off passengers
On/off location	Location of a picking up/droping off
Cruise distance	Non operating cruise distance before picking up
Occupied distance	Operating distance from a picking up to its dropping off
Fare	Fare of a metered trip

Combination of the fields of *Cruise Distance* and *Occupied Distance* tells the distance a taxi travels, which can be used for our later analysis.

For better understanding battery aging phenomenon, we also perform a field investigation on EV taxi drivers. *Information involved in 30 EVs are collected, mainly including each EV's time of putting into market and battery replacing.* Putting into market represents the initial state of EV battery, which records EV battery's integrated life span together with battery replacing time.

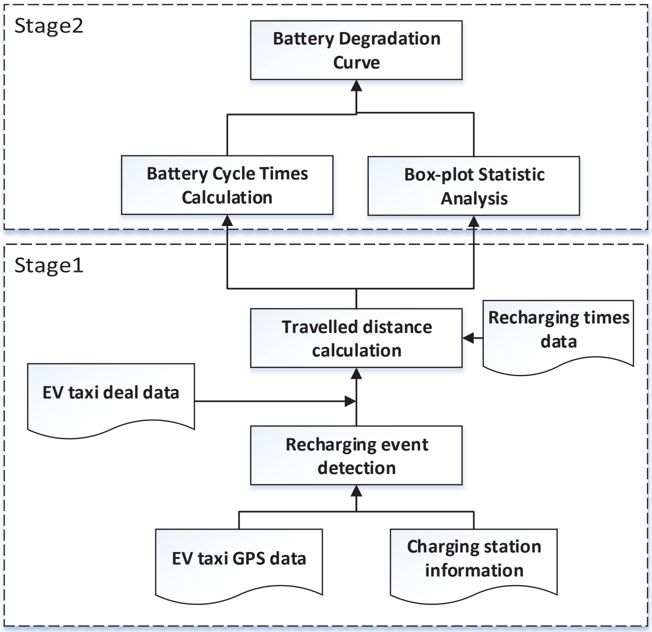

Fig. 2. Solution Framework

IV. Methodology

A. Solution Framework

In this section, we propose the solution to the battery degradation understanding and the framework is shown in Figure 2.

The framework takes three datasets as inputs, including charging station information, EV taxi GPS and deal data. Charging station information refers to where a charging station (CS) locates and how many charging points are deployed in this CS. We firstly perform recharging event detection by utilizing CS information and EV taxi GPS records. Thereafter, travelled distance between two consecutive recharging event (TDC) can be obtained by combining detected recharging event and EV taxi deal data. Then we make a statistic analysis based on box-plot and use recharging times as supplements to explore battery degradation. Besides, battery cycle times can be calculated by integrating TDC into power consumption per hundred kilometers. And finally, the battery degradation curve in real-life EV use can be plotted and compared with the official one.

B. Travelled Distance Between Consecutive Recharging Events

Combining the recharging event and deal records of EV taxis, their TDC can be calculated. The result is shown in Figure 3.

In figure 3, the X-axis denotes the value of travelled distance while the Y-axis defines its cumulative distribution function (CDF). It can be obviously observed that most of EV taxi drivers travel 140$\sim$180 kilometers between two consecutive recharging events, although the EV taxi company declares the maximum trip distance per full-charging of an EV taxi is 300 kilometers.

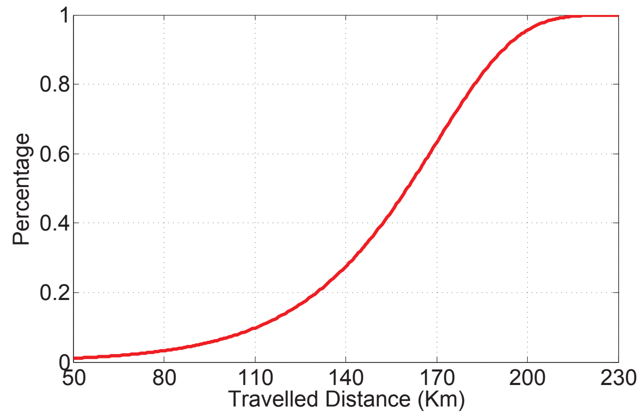

Fig. 3. Empirical CDF Distribution of Travelled Distance

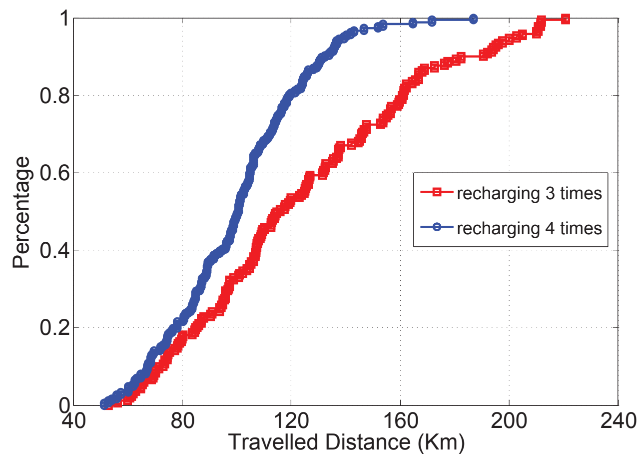

Fig. 4. Travelled Distance Comparison Between Two Categories Of EV Taxis

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

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

We still use CDF to analyze their distributions of travelled distance between two consecutive recharging events and it's clear that those recharging 3 times per day can travel more distance than those recharging 4 times. Actually, the main difference between them is their time when those EV taxis are put into market. Most of those recharging 4 times per day are put into market for operating a year earlier than those

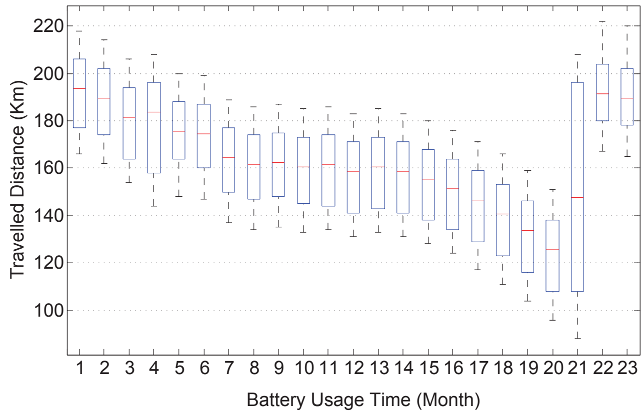

Fig. 5. Box-Plot For Travelled Distance Distribution

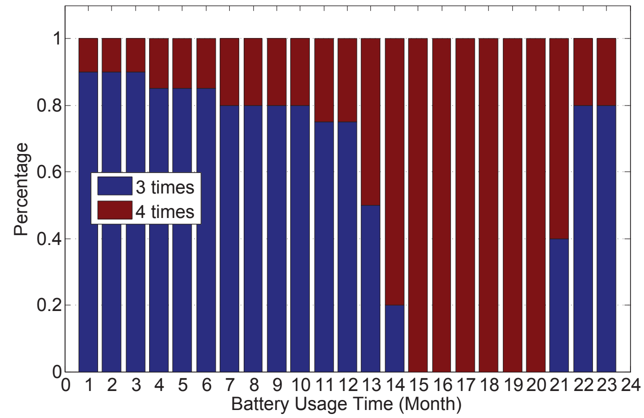

Fig. 6. Bar-Stack For Recharging Times Distribution

charging 3 times per day. The implication is that: *battery capacity decreases significantly over time, leading more charging times and less travel distance per full-charged.*

C. Statistic Analysis Methods For Exploring Battery Aging

Based on above analysis, TDC can be selected to characterize battery degradation phenomenon. For better understanding battery aging, some proper statistic analysis methods should be proposed.

We use the 30 EV taxi set mentioned in section III as samples to observe their travelled distance distributions. Statistic analysis based on the box-plot is presented and the distribution of a randomly selected sample EV taxi is shown in Figure 5.

In figure 5, the X-axis denotes the battery usage time and we use one month as a time interval. Each box-plot responds to the TDC distribution in one certain month. Since the sample EV taxi is chosen from the 30 EV taxi set, its time of replacing battery can be determined. It can be obviously observed that TDC of the sample EV taxi decreases as battery usage. Specifically, in the first few months, TDC of this sample EV taxi mainly falls in the range of 180∼210 kilometers, while this value drops down to 110∼140 kilometers in the last few months, depicted as box-plots corresponding to 18,19 and 20 in X-axis.

It should be noticed that TDC values represented by the box-plot corresponding to 21 in X-axis range from 60 to 210 kilometers, significantly distinguished from other box-plots in range span. The reason for that lies in the fact that the sample EV taxi replaces its battery on some day in the 21st month. Specifically, TDC of the sample EV taxi keeps a low value as the box-plots corresponding to 18,19 and 20 shows before the battery replacing day, while it approaches to a high value like the first few box-plots displays after battery replacement. Then in the 22st and 23st months, the sample EV taxi can travel a relative long distance due to the battery replacement.

Besides, recharging times per day (RTPD) is also introduced in the statistic analysis to prove the battery aging further. For this sample EV taxi, its information of RTPD is collected and shown in Figure 6. It can be observed that in the first few months, this sample EV taxi mostly recharge 3 times per day, while in the last few months, this recharging behavior pattern is totally replaced by recharging 4 times per day.

Other samples from the 30 EV taxi set share the similar statistical property with the above discussed one. Therefore, our statistic analysis methods utilizing TDC and RTPD are beneficial for understanding battery degradation phenomenon in real-life EV use.

D. Battery Cycle Times Calculation

Battery cycle times is a significant index for battery degradation analysis. One time battery cycle refers to the process of battery's full-charge state to running-out state. In this study, EV taxi drivers rarely use up battery power before recharging. Actually, they will reserve certain amount of battery power so that they can reach CSs before recharging, however, BMS data is not open in pubic, thus battery cycle times can not be calculated directly.

Battery power consumption can be used for this calculation. Specifically, for the EV type analyzed in this paper, we use *Pow* to represent its power consumption per hundred kilometers and *Dis* as its travelled distance. Since battery capacity *Cap* is known for us, thus the battery cycle times *Cyc* can be computed as

$$Cyc = \frac{Pow \times Dis}{Cap} \tag{1}$$

Charging facilities can also be taken into consideration when calculating battery cycle times. Specifically, we use P to represent power delivered from the charging station and T as EV taxis' recharging time (obtained from recharging event data), then the battery cycle times *Cyc* can be computed as

$$Cyc = \frac{P \times T}{Cap} \tag{2}$$

We use the average value of Equation 1 and Equation 2 as the final value of *Cyc*.

V. Experiments and Results

A. Evaluations on Battery Performance

The professional standards of battery performance mainly include battery cycle times and battery-supported maximum driving distance. In order to obtain those two values of real-life EV use, box-plot method based on statistical analysis and corresponding recharging frequency analysis are applied to the EV taxi fleet in Shenzhen. Except for that 30 EV taxi set mentioned in section III, about 800 EV taxis are used for calculating their battery cycle times and battery-supported maximum driving distance. The results is shown in Table IV.

TABLE IV
Result Comparison of Battery Performance

	real-life use	laboratory test
Temperature	0 °C-40 °C	20 °C
Charging Rate	fast charging	fast charging
Depth of Discharge	70%	100%
Road Condition	real	simulated
Battery Cycle Times	1086	3200
Battery-supported maximum driving distance	216000 Km	400000 Km

Based on industry standard, the battery needs replacing when its capacity drops down to 80% of the initial state. In this study, TDC can be used for battery performance evaluation despite lacking of BMS data. It can be obviously observed that battery decays faster in real-life use than experimental environment test, reflecting on the huge reduction on battery cycle times and battery-supported maximum driving distance.

Actually, battery capacity loss can be influenced by many factors displayed in Table IV, including environmental temperature, charging rate, depth of discharge and real-life road condition. Laboratory test keeps a constant temperature while in real life battery undergoes a process of season change, especially in extreme circumstance of hot and cold. Besides, real-life road condition is also a significant factor in battery aging, mainly focusing on traffic congestion. And finally, depth of discharge can not be ignored. In laboratory test, battery is recharged until it's used up while in real-life battery always maintains an amount of power from drivers' own initiative. These factors accelerate battery aging in real-life EV use.

B. Evaluations on Battery Degradation Curve

Due to lacking of BMS data, TDC will be a substitution of battery capacity for battery degradation curve evaluation. Specifically, for an EV taxi, its TDC box-plot corresponding to a certain month is firstly selected, then TDC values ranging from 3/4 of the chosen box-plot to the top are collected since those part of data can reflect battery performance better. We use the average value obtained from the collected TDC values to represent the battery capacity of this EV taxi in the selected month. A same process is performed on other EV taxis, thus we can obtain an average value set. Thereafter, we make an average computation for this set again and use battery cycle times to substitute months. The final result is shown in Figure 7.

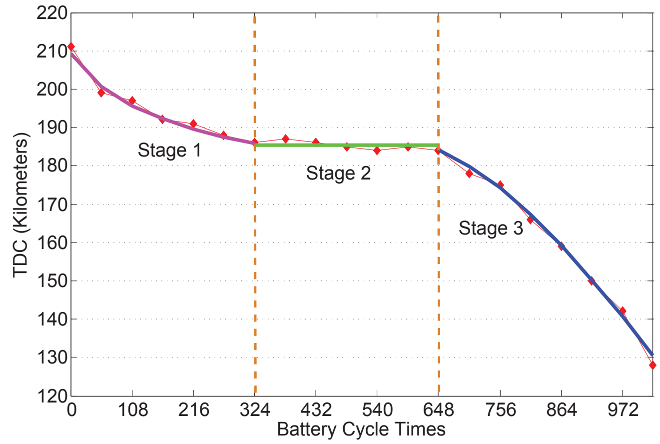

Fig. 7. Battery Degradation Curve In Real-life EV Use

Battery degradation process can be divided into 3 stages based on battery aging speed. As shown in Figure 7, we use different color to represent different stage. Specifically, the process of battery degradation ranging from 0 to 324 is called slow degradation phase, remarked by stage 1. While stage 2 is called stable degradation phase since the battery capacity loss is close to zero. Compared to that, stage 3 depicts a fast battery degradation process and TDC values rapidly drop to a low level, leading to the range anxiety of EV taxi drivers.

We use a segmented function to fit this battery degradation process and the equation is shown in Equation 3, where the parameter x refers to the battery cycle times.

$$TDC = \begin{cases} 209.3 * x^{-0.06127} & 0<x<324 \\ 185.5 & 324<x<648 \\ 188.3 * e^{-\frac{(x-10.71)^2}{15.36}} & 648<x<1026 \end{cases} \tag{3}$$

C. Evaluations on Driving Behavior's Impact in Battery Degradation

Figure 7 reflects an average level of the battery degradation of the EV taxi fleet while in this subsection, we put an emphasis on individual performance. Specifically, for an individual EV taxi, we still utilize a segmented function to fit its battery degradation process and then compare it with the average level. The results are shown in Figure 8

As shown in Figure 8, two typical samples are selected to be compared with the average level, respectively remarked by blue and green curves while the dashed red one depicts the average level of the battery degradation process. The blue curve is above the dashed red one, indicating the battery degradation rate corresponding to the blue one is slower than the average level while the green curve is below the average level, illustrating a faster degradation process. Although only two typical samples are extracted, we can actually perform a similar function fitting for every EV taxi. The fitting results indicates that 44.0% of the whole EV taxi fleet is above the average level while 51.0% is below. Since they operate in the same city, meaning the external circumstance, such as road condition, temperature and recharging rate, differs little,

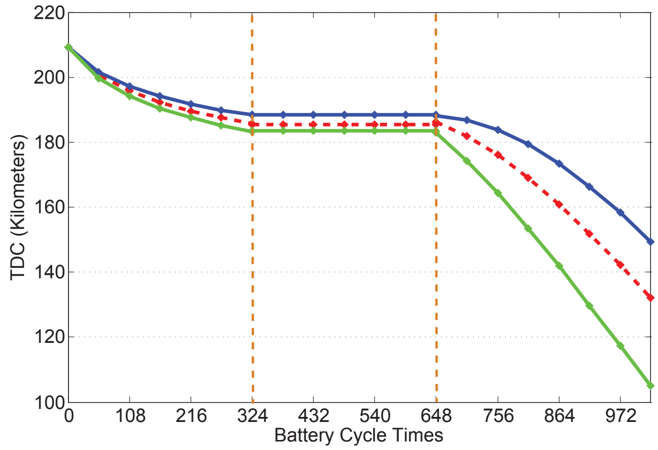

Fig. 8. Battery Degradation Comparison for different EV taxi individual

reasons for these different battery degradation rates mainly lie in their different driving behaviors.

In this study, an EV taxi driver's driving speed is collected to depict his driving behavior. For those above the average level of battery degradation, we observe that their driving speeds keep on 70 Km/h at most time, meaning that this driving speed is nearly optimal in real-life EV use, beneficial for slowing down the battery degradation rate.

VI. Conclusion

In this study, by utilizing GPS and deal records of EV taxis operating in Shenzhen, China, we explore the battery degradation phenomenon in real-life EV use. Firstly, an amount of typical EV taxis are extracted as samples to explore battery degradation, while their recorded data during entire battery life is collected. Then travelled distance between two consecutive recharging events is selected to characterize battery degradation phenomenon, as well as recharging frequency. And finally a statistic analysis based on box-plot is proposed to understand battery aging. Our experiments demonstrate that external circumstances, such as temperature, road condition and charging rate, will have an impact on battery degradation in real-life EV use while the overall battery aging trend will be affected little.

In the future, we would like to analyze the battery degradation phenomenon in a more fine-grained way. Multiple impacting factors such as temperature, depth of discharge and charging rate should be used as parameters to form a model on battery capacity fade estimation. Besides, effect of real-world driving styles in an EV battery performance and aging can also be analyzed and simulated.

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