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ANALYSIS ON INFLUENCE FACTORS OF ENERGY CONSUMPTION OF ELECTRIC VEHICLES BASED ON REAL-WORLD DRIVING DATA

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ABSTRACT

With the large-scale penetration of electric vehicles, the research on the influence factors of energy consumption of electric vehicles has become an important requirement for the estimation of energy efficiency, energy-saving route planning and the optimal design of power system structure. In this paper, the real-world driving data of 59 electric taxis in Beijing are obtained and divided into three-level driving fragments. The influence factors of energy consumption, including vehicle-related factors (velocity, acceleration and kinematic states), environment-related factors (ambient temperature and traffic condition) as well as driver-related factors are extracted and studied. Results show that the energy consumption of electric vehicle is significantly influenced by velocity, acceleration and kinematic states. Benefit from the energy-saving at idling state and the braking energy regeneration technology, traffic congestion has a slighter influence on energy consumption. Besides, the appropriate ambient temperature around 19.5 ℃ and moderate driving pattern can help reduce energy consumption to a certain extent. This work builds an essential foundation for accurate estimation and prediction of energy consumption of electric vehicles.

Keywords: electric vehicles, energy consumption, influence factors, real-world driving data

NONMENCLATURE

Abbreviations	
EVs	Electric vehicles
NEVs	New energy vehicles
ICEVs	Internal combustion engine vehicles
DCs	Driving cycles

Symbols	
ECR	Energy consumption rate
ERR	Braking energy regeneration rate

1. INTRODUCTION

In recent years, electrification of transportation has been widely recognized as an imperative measure towards the targets of emissions reduction and energy efficiency improvement [1]. With the announcement of the three-year action plan aims for blue skies, the number of New Energy Vehicles (NEVs) in China had reached 2.61 million by the end of 2018. However, limited by the battery technology, electric vehicles (EVs) have limited endurance mileage and long charging process, which have become the main obstacles in the application of EVs. Considering the limitations of EVs, the analysis and accurate estimation of the energy consumption of EVs under real-world driving conditions has become a key performance index of great concerns to electric vehicle (EV) drivers, automakers and policy-makers, as it significantly affects energy efficiency, environmental and economic benefits of the EV transportation system, and provides strong support for the energy-efficient routes planning as well as battery size optimal design.

The analysis of energy consumption influence factors is regarded as the important foundation of the accurate estimation of energy consumption. As a result of the difference of propulsion systems between EVs and the internal combustion engine vehicles (ICEVs) as well as the application of braking energy regeneration technology, the characteristics and influence factors of energy consumption of EVs differ from ICEVs to a large extent. In recent years, numerous researches have

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focused on the study of influence factors and estimation of energy consumption for EVs.

The commonly used methods for energy consumption analysis can be summarized into two categories: data-driven and model-driven methods. The model-driven methods in previous researches mainly include ‘engine to wheel’ models and ‘wheel to engine’ models [2]. Drivers’ operations are captured as input and connected with vehicle torque and power in the ‘engine to wheel’ models, which are widely used to study the performance and fuel consumption in vehicle industry. On the contrast, the traction requirement at the wheels are calculated first and connected to engine in the ‘wheel to engine’ models. So, the collected vehicle characteristic data as well as driving cycles (DCs) can be used as input parameters for energy consumption estimation. In data-driven methods, massive real-world driving data fused with road, weather and traffic information are used to accurately estimate and predict the energy consumption of EVs at complex driving conditions using various statistical methods and machine learning algorithms [3].

Benefit from the electrification of transportation and the rapid development of internet of vehicle (IOV), the collection of vehicle data has become more feasible, and real-world driving data fused with environmental and traffic information are widely used for measurement and estimation of energy consumption of EVs. Besides, in order to take the influence of the traffic conditions and infrastructure design into account, many researchers construct DCs based on real-world driving data to assist the study of energy consumption [4].

Based on previous studies, the influence factors of energy consumption can be summarized into three categories, vehicle-related factors [5-6] (state of health (SOH) of battery, braking energy regeneration and auxiliary system energy consumption), environment-related factors [7-8] (ambient temperature, wind speed, road condition and traffic condition) and driver-related factor [9-10] (driving pattern and charging habits). Results show that the degradation of battery, the use of auxiliary system, head wind, low temperature and larger road slope will significantly increase the energy consumption. In the contrast, the use of braking energy regeneration technology and a moderate driving behavior can reduce energy consumption by a certain degree.

In this work, massive amounts of real-world driving data of electric taxis in Beijing are used to provide further support for accurate estimation and influence factors analysis of energy consumption for EVs. Based on statistic methods, vehicle-related, environment-related and driver-related factors are taken into consideration and the exact effects on energy consumption are studied.

The remainder of this paper is organized as follows: section 2 describes the process of data collection and preparation. Influence factors of energy consumption are analyzed in section 3. Conclusions are given in section 4.

2. DATA PREPARATION

The data used in this paper come from National Monitoring and Management Platform for New Energy Vehicles (NEVs), which can monitor the real-time running condition and store all historical running data of EVs including electric taxis, electric buses, electric sanitation vehicles and electric logistic vehicles nationwide. By Sep. 2019, the number of monitored vehicles in the platform had reached 2.6 million. To support the research on energy consumption in this paper, 59 electric taxis running in Beijing are selected from the platform as the research objects for the reason that the driving mileage and driving characteristics of taxis are relatively stable and regular, which makes the extraction of influence factors of energy consumption more feasible. Historical running data recorded on 1 Hz of these vehicles from 2017 to 2018 are obtained from the platform, each row in the data table represents a frame of data uploaded by the monitored vehicles, mainly include time, velocity, current, voltage, SOC, longitude and latitude, etc. The technical information of these electric taxis is listed in Table 1.

Table 1 The technical information of electric taxis used in this paper

Parameters	Value
Brand	BAIC
Model	EV200
Curb weight	1295kg
Maximum velocity	125km/h
Range	200km
Battery capacity	91.5Ah, 30.4kWh
Battery weight	291kg
Battery material	Ternary polymer lithium
Motor power	30/53kW
Energy consumption	14.5kWh/100km
Charging time	0.5h (fast charging to 80%); 8-9h (slow charging to 100%)

The raw data table contains the data of charging and driving state. In this paper, the driving data are identified and extracted from the raw data table then fused with the environmental information including weather data and traffic condition data collected from network based on driving time and trajectory matching.

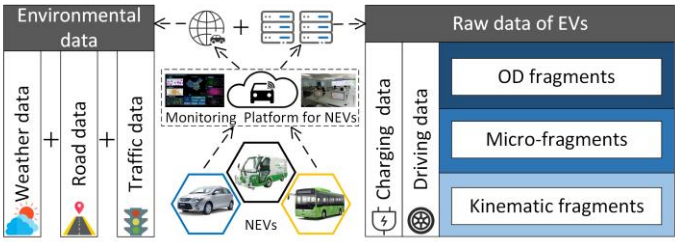

Fig 1 The data collected from the platform and network

For the convenience of energy consumption analysis, according to the driving characteristics, the driving processes are divided into three levels of fragments:

①OD fragment: The driving process from origin to destination;

②Micro-fragment: The driving process between two adjacent idling states;

③ Kinematic fragment: The driving process with certain range of velocity and acceleration.

For each driving fragment, energy consumption rate (ECR) and braking energy regeneration rate (ERR) are calculated based on the integral of the product of voltage and current, then fused with driving data.

$$ECR = \frac{\sum_{i}^{N}\{U_i I_i t_{\text{interval}} \mid I_i > 0\}}{3.6\times10^6 M}(kWh/km) \quad (1)$$

$$ERR = \frac{\sum_{i}^{N}\{U_i I_i t_{\text{interval}} \mid I_i < 0\}}{3.6\times10^6 M}(kWh/km) \quad (2)$$

where, $U_i(V)$ and $I_i(A)$ are voltage and current at time i, t_{interval} is the time interval between two frames of driving data, which equals 1s here, $M(km)$ is the driving mileage of the driving fragment. It should be noted that the current direction during braking energy regeneration is from motor to battery, which is opposite to the direction of normal discharging state. So, the current at braking energy regeneration state and ERR are defined as negative.

3. ENERGY CONSUMPTION ANALYSIS AND DISCUSSIONS

The nominal energy consumption of EVs used in this paper provided by automakers is 14.5 kWh/100km. Based on the statistic of real-world driving data, the real-world ECR and ERR are 19.62 and -3.59 kWh/100km respectively, and the characteristics of energy consumption can obviously be different between vehicles under different driving conditions.

Using the obtained three-levels driving fragments fused with energy-related and environmental information, the influence of vehicle-related, environment-related as well as driver-related parameters on energy consumption are analyzed respectively in the following sections.

3.1 Kinematic fragments

Influenced by driving conditions and drivers' operations, the vehicle shows different driving states represented as the different combinations of velocity and acceleration during driving processes. As shown in Fig 2, a typical trip consists of several micro-fragments with different velocity and length. According to the range of velocity and acceleration, each micro-fragment is further divided into five kinds of kinematic fragments including starting, accelerating, cruising, decelerating and idling fragments. The division criteria of kinematic fragments are determined based on the statistic of all driving data and listed in the Table 2.

Table 2 Criteria of kinematic fragments division

Kinematic states	Velocity	Acceleration
Starting	>=0km/h (starting from 0km/h)	>0.15m/s^2
Accelerating	>4km/h	>0.15m/s^2
Decelerating	>4km/h	<-0.15m/s^2
Cruising	>4km/h	>=-0.15m/s^2 & <=0.15m/s^2
Idling	<=4km/h	--

The driving time, driving mileage, ECR and ERR of different states are calculated and shown in Fig 3. The ratio of energy consumption to driving mileage of different states in descending order is as follows: idling > starting > accelerating > cruising > decelerating.

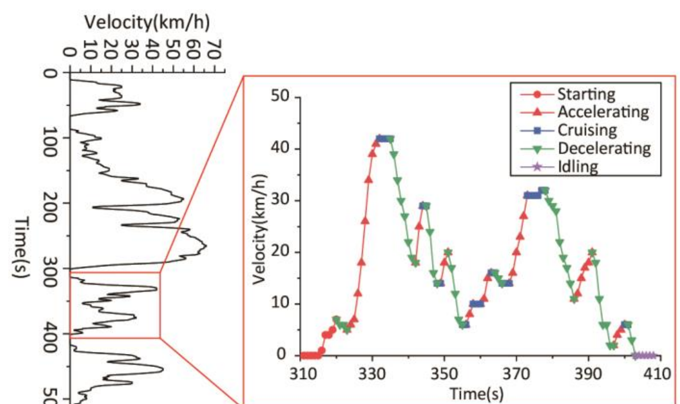

Fig 2 Example of micro-fragments and the corresponding kinematic fragments

The states of starting and accelerating consumes the most energy reaches 81.45%, and starting from stationary state consumes more energy than accelerating at moving state. The energy regeneration almost entirely occurs at decelerating state, and the corresponding energy consumption is the lowest among all states. The driving time and energy consumption proportion of idling state reaches 23.26% and 4.06% respectively, however the driving mileage proportion is close to 0. Due to the stop of motor at idling state, the energy consumption mainly results from the use of auxiliary system.

As a result of different characteristics of different states, the proportion, frequency and length of different kinds of kinematic fragments in micro-fragments or OD fragments can obviously affect the energy consumption and can be extracted as crucial parameters in the estimation as well as prediction of energy consumption using DCs.

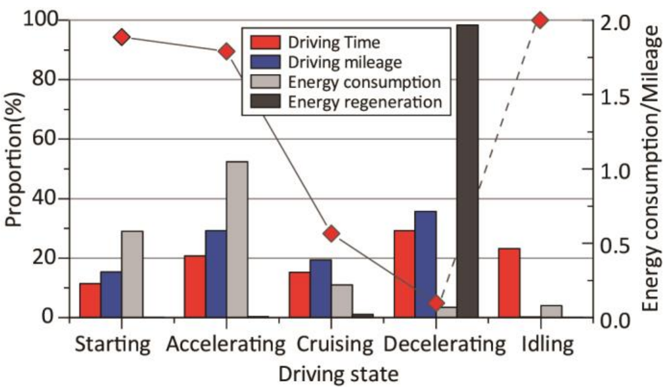

Fig 3 Distribution of driving time, driving mileage, energy consumption and regeneration at different states

3.2 Velocity & acceleration

Velocity and acceleration are the most intuitive parameters describing the running state of vehicle, and highly related to the power output of battery and motor. In this paper, the acceleration data at each moment is calculated based on velocity data of adjacent rows as formula (3) shows, for the acceleration information is not included in raw data items.

$$a_i = \frac{v_{i+1} - v_i}{t_{i+1} - t_i} \times \frac{1000}{3600} = \frac{v_{i+1} - v_i}{3.6}, i = 1,2,...,k-1 \tag{3}$$

To research the influence of velocity and acceleration at different driving states, the energy consumption analysis is carried out on the kinematic fragment level in this section. For each kinematic fragment, the statistic of average velocity and acceleration are applied, then the relationship with ECR as well as ERR of battery, motor and auxiliary system are studied respectively.

The relationship between velocity and the ECR, ERR at the states of starting, accelerating, cruising and decelerating are shown as (a), (b), (c), (d) in Fig 4 respectively. Results show that the general trends of ECR and ERR increase with the increase of average velocity initially and reaches peak in the range of 30-40 km/h then decrease at the states of starting, accelerating and decelerating. According to the analysis of motor data, the position and value of the peak ECR are related to the external characteristics of the vehicle motor.

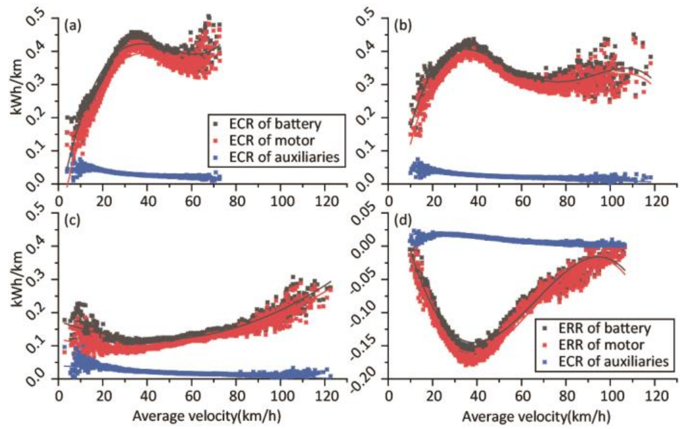

Fig 4 Relationship of average velocity with ECR and ERR at different states ((a): starting, (b): accelerating, (c): cruising, (d): decelerating)

As for cruising state, the ECR of battery and motor decreases with the increase of average velocity initially then increases gently. The ECR of auxiliary system declines slightly with the increase of velocity. At different kinematic states, the proportion of energy consumption of auxiliary system to total energy consumption changes from 3% to 30%.

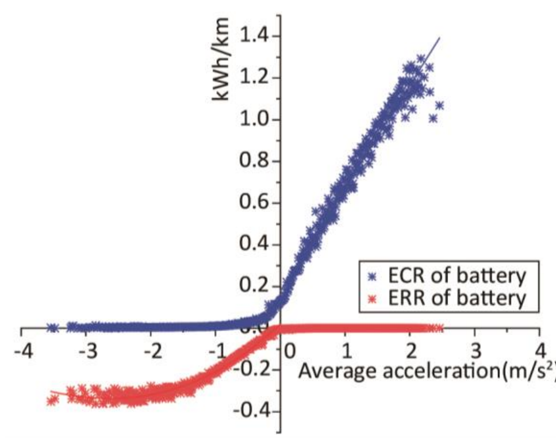

Fig 5 Relationship of average acceleration with ECR and ERR of battery

Using the driving data at starting, accelerating and decelerating states, the relationship between acceleration and ECR, ERR is studied. As shown in Fig 5, ECR presents a significant linear relationship with acceleration, and the ECR can even exceed 1 kWh/km at high acceleration. The ERR increases with the increase of the absolute value of deceleration initially, then becomes relatively stable at 0.33 kWh/km, which is related to the limitation of energy regeneration capability of battery.

3.3 Ambient temperature

Ambient temperature data in Beijing are obtained from network and fused with driving data based on time matching, then the relationship between energy consumption and ambient temperature is studied on the micro-fragment level.

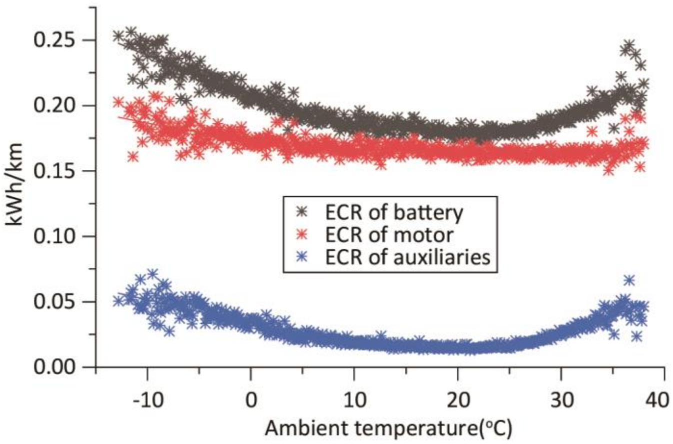

Fig 6 Average ECR of battery, motor and auxiliaries at different ambient temperature

As shown in Fig 6, the average ECR of battery, motor and auxiliary system at different temperatures are calculated from all of the micro-fragments and shown in black, red and blue respectively. From the fitting polynomial curves, the change of ECR of motor is not obvious with the increase of temperature. The fitting curves of ECR of battery and auxiliary system present 'U' shapes, with the lowest ECR occurring at 19.5℃. The reason for this phenomenon is that the usage of air conditioner (AC) at low and high temperature consumes a substantial part of energy, accounting for about 12-30% of the total. Besides, low temperature has passive effects on capacity as well as internal resistance of battery, which will limit the output performance and increase the energy consumption for heat generation.

It can be summarized that the impact of ambient temperature on EV energy consumption derives from two aspects: the use of auxiliary system and the performance differences of battery at different temperatures.

3.4 Traffic condition

By the end of 2018, the number of automotive vehicles in Beijing had reached 6.08 million. The large amounts of vehicles can bring severe challenges to urban road traffic. According to the research results of Beijing transportation development annual report 2019, the average daily time of severe congestion, moderate congestion, mild congestion, basic free-flow and free-flow were 0.25 hours, 2.58 hours, 3 hours, 7.34 hours and 10.83 hours respectively in 2018. The traffic congestion can reduce the efficiency of traffic transportation and raise the fuel consumption of ICEVs by 18%~65% compared with the free-flow scenario [8].

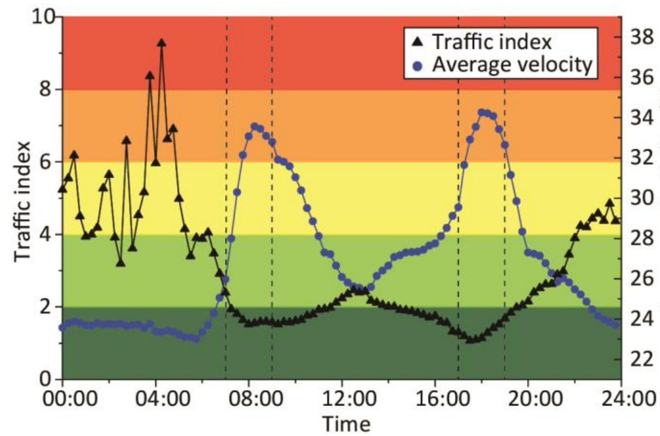

Fig 7 The distribution of traffic index and average velocity of weekdays in Beijing

Fig 7 shows the typical case of distribution of traffic index of weekdays in Beijing, which is an index provided by Beijing Municipal Commission of Transport based on all of the roads in Beijing to quantify the real-time traffic condition. According to the traffic index, the state of traffic condition can be classified into five categories as Table 3 shows. It can be seen from Fig 7 that the traffic indexes during morning rush hours (from 7 a.m. to 9 a.m.) and evening rush hours (from 5 p.m. to 7 p.m.) are obviously higher, and the corresponding average velocity is 23.7 km/h, significantly lower than non-rush hours.

Table 3 The traffic index range and corresponding traffic condition

Traffic index	Traffic condition
[0,2)	Free-flow
[2,4)	Basic free-flow
[4,6)	Mild congestion
[6,8)	Moderate congestion
[8,10]	Severe congestion

To research the relationship between traffic condition and energy consumption, the average ECR during rush hours and non-rush hours on weekdays and weekends are calculated and shown in Fig 8. Differently from the significant influence of traffic congestion on fuel consumption of ICEVs, the influence of traffic condition on energy consumption of EVs is slighter. The reasons can be summarized as follows: the kinetic and potential energy can be effectively collected and recycling stored benefits from the application of braking energy regeneration technology. Besides, the motor can completely stop rotation and consumes zero energy at idling state, which can help save energy at the frequent idling state during traffic congestion.

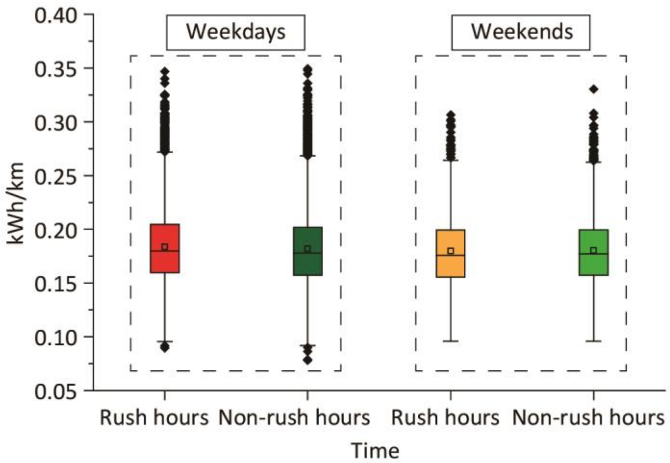

Fig 8 The ECR of electric vehicles during rush hours and non-rush hours on weekdays and weekends

Considering the specific influence of traffic conditions on EVs, the impact of vehicle electrification on the overall energy consumption of the transportation and the traffic and environmental protection-related policies can be discussed in depth.

3.5 Driving pattern

Driving pattern can be defined as the instantaneous decisions of the drivers to cope with the real-time driving condition, especially how drivers apply pressure on acceleration and brake pedal. The driving pattern is attributable to several factors include personal characteristics, vehicle model, traffic and road conditions. In this paper, considering the operation rules of electric taxis, driving pattern analysis is done based on the acceleration distribution of daily driving data and the energy consumption of corresponding micro-fragments.

The operation frequency and intensity of acceleration and brake pedal are important driving pattern characteristic parameters and can be quantified by the distribution of acceleration and deceleration data. In this paper, the acceleration distribution parameters, including 95% quantile of acceleration and 5% quantile of deceleration, are proposed and used to distinguish the different driving patterns.

As Fig 9 shows, the distribution of 95% quantile of acceleration and 5% quantile of deceleration on different days between vehicles are different. Based on the average values of these two parameters, the driving pattern can be classified into four categories:

①HaHd (High acceleration & High deceleration)

②HaLd (High acceleration & Low deceleration)

③LaHd (Low acceleration & High deceleration)

④LaLd (Low acceleration & Low deceleration)

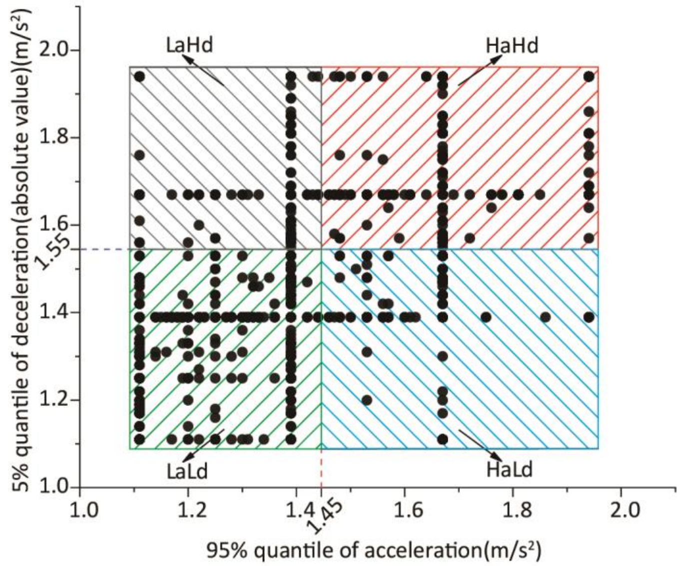

Fig 9 The distribution of 95% quantile of acceleration and 5% quantile of deceleration of daily driving data

The corresponding ECR of different driving patterns are calculated and shown in Fig 10. Results indicate that the ECR of ‘LaLd’ driving pattern is the lowest among all driving patterns, and that of ‘HaHd’ is the highest. The ECR of ‘HaLd’ driving pattern is slightly higher than ‘LaHd’ driving pattern, which indicates that the impact on energy consumption of high acceleration is greater than high deceleration.

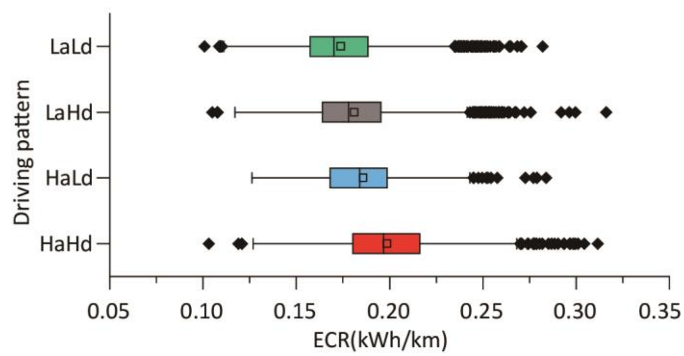

Fig 10 The distribution of ECR of different driving patterns

So, the conclusions can be drawn from the analysis of driving pattern that moderate driving pattern with smoother accelerator and brake pedal position adjustment during driving process can effectively reduce energy consumption.

4. CONCLUSION

The influence of vehicle-related, environment-related and driver-related factors on energy consumption of electric vehicles is studied based on real-world driving data fused with environmental information of 59 electric taxis in Beijing. According to the multi-level fragment analysis results, several key points can be summarized as follows:

- Starting and accelerating states consume 81.45% energy, and the ratio of energy consumption to driving mileage can be ranked as: idling > starting > accelerating > cruising > decelerating.
- Linear and nonlinear relationships exist in velocity and acceleration with ECR and ERR, and the impact is related to the external characteristics of vehicle motor.
- Benefit from braking energy regeneration as well as the zero-energy consumption of motor at idling state, the influence of traffic congestion is slighter compared to ICEVs.
- A nonlinear relationship exists in ambient temperature and energy consumption, and represented as the U-shape curve with the lowest ECR occurs at 19.5℃.
- The moderate driving pattern with appropriate frequency and intensity of acceleration and brake pedal operations can effectively reduce energy consumption.

This work builds an essential foundation for accurate estimation and prediction of energy consumption of EVs. In further work, the influence of multi-factor coupling will be studied, and the energy consumption estimation and prediction model will be constructed.

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