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Battery electric vehicle usage pattern analysis driven by massive real-world data

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A B S T R A C T

Electric vehicles (EVs) are playing a key role in supporting transportation electrification and reducing air pollution and greenhouse gas emissions. The increased number of EVs may also bring about some issues concerning energy system structure optimization and efficiency enhancement. User behavior analysis and simulation is an important method to solve these issues. A stochastic model for describing the usage of vehicle is essential to handle simulation models and behavior models. Therefore, a more comprehensive understanding of EV usage patterns is necessary for the model establishment. The paper focuses on the 2,047,222 charging events and 8,382,032 travel events collected from 26,606 battery electric vehicles operating in Beijing, China, in 2018, based on the open lab of National Big Data Alliance of New Energy Vehicles. With the large-scale data resource rather than limited samples, we provide some robust statistical results and some multi-dimensional comparative analysis in the paper, which can be applied in large-scale deployment environments and large population cities. The results can also provide information for charging infrastructures construction, gird management, vehicle charging scheduling, and so forth in Beijing and even other metropolises with similar situations.

1. Introduction

Environmental pollution and greenhouse gas emissions generated by the transportation industry have recently attracted widespread attention in different countries all over the world [1]. Electric vehicles (EVs) are widely considered as the most promising alternative to internal combustion engine vehicles (ICEVs) towards cleaner transportation [2]. Battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) are both efficient solutions for the electrification of light-duty vehicles. Fully aware of the interaction between the market diffusion of EVs and charging infrastructures, the Chinese government has issued a series of financial incentive policies to implement a national charging network; this is among the largest deployment programs in the world [3]. EV charging electricity demand also can be a flexible load for optimizing and regulating the operation of the power grid [4–6]. Therefore, investigating EV usage patterns is a continuing concern within the deployment and operation of the EV charging infrastructures.

A number of alternative solutions based on advanced information technologies have materialized and are rapidly evolving in recent years, providing a new motivation for monitoring and managing of grid operations and EV schedules. The integration of EVs and information technologies is creating crucial opportunities as well as challenges for China. People can find valuable information through knowledge discovery technologies for travel event characteristics, charging event characteristics, and user preferences based on abundant data resources [3]. This possibility motivates us to carry out the research of this paper from the following two aspects:

(1) Firstly, to inform EV designs of automakers and assess the environmental benefits of transportation electrification efficiently, a necessary foundation is to analyze the travel habits of EV users [7,8]. Previous researchers mainly focused on the travel pattern analysis formed by successive activity

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locations over a period (such as a day), which is a part of the usage pattern [9]. Dimensions of analysis mainly include daily distance, single-trip distance, travel duration, travel time, energy consumption, *etc.* [10,11].

(2) Secondly, EV charging process simulation is addressed to optimize and regulate the power grid in previous studies. Understanding the charging profile of EV users can be a basis to establish a charging process simulation model [12,13]. Individual trip chains and multi-agent systems are two mainstreams to simulate the EV operation process [14,15]. Charging time, charging stage-of-charge (SOC), duration between charging, and characteristics of the traveling pattern can be extracted to describe the charging profile of EV users. When considering the vehicle-to-grid (V2G) process or optimizing charging decision-making process, charging availability and grid power generated by EVs should be analyzed to achieve the participation of EVs [16–19].

Nevertheless, extracting necessary and valuable elements to provide comprehensive usage pattern statistical results from low-value initial operating data of EVs is an important and meaningful topic [19–22]. In the early stage of EV development, some studies applied the usage pattern of ICEVs to infer that of EVs. Nathaniel S. Pearrel et al. [8] inferred and simulated the EV driving pattern based on 484 instrumented gasoline vehicles. They focused on the question "Are battery-range limitations compatible with our gasoline-enabled driving habits" to analyze the data. Hua Cai et al. [23,24] evaluated the impact of travel patterns on the development of public charging infrastructures based on the big-data collected from 11,880 taxis and analyzed the greenhouse gas implications of fleet electrification in Beijing. Moreover, the *Transport tEchnology and Mobility Assessment* platform is designed for harnessing the potential of the big data in the field of transportation policies in Europe. De Gennaro et al. analyzed 28,000 vehicles from this platform with different energy sources for large-scale characteristics statistics, energy demand estimation, and carbon emission assessment [25]. Nevertheless, using ICEVs instead of EVs to analyze the characteristics cannot fully reflect the usage pattern of EV users.

Many prior works applied travel surveys to extract the characteristics of the EV usage pattern. Based on the statistical result of more than 180 EVs collected from the Danish "Test-en-Elbil" ("Test-an-EV") project, Pedersen et al. compared different usage pattern characteristics between EVs and ICEVs [26]. They also calculated the potential and capacity of V2G based on the simulation of usage pattern characteristics generated from the National Household Travel Survey (NHTS) [27]. However, the single travel distance was assumed the same in different time buckets of the day in this study. To forecast the charging demand of EVs, charging start time, charging power, *etc.*, were utilized to simulate the charging behavior [28]. They described the distribution of the charging start time with a Gauss distribution. No matter the motivation, when the abundant operating data resource is hard to obtain, it is an efficient method to establish the research database with surveys. A major advantage of the survey is that researchers can obtain some attributes of EV users (*e.g.*, gender, age, *etc.*) in detail, which cannot be reflected from the operating data intuitively. Nevertheless, some stochastic characteristics of the usage pattern may be neglected in the analysis based on the travel surveys [29].

For the vehicle operating data analysis, Weldon et al. analyzed 72 personal BEV users about the Irish usage pattern with the interquartile range (IQR) approach [30]. The analysis fully illustrated the user behavior of BEVs in small and medium-sized cities and regions. Because Ireland is a small population city and its analysis results may not be suitable for large metropolises like Beijing. Xu et al. analyzed the seasonal impact on the usage pattern based on 197 BEVs operating in Beijing, collected from technical specifications of remote service and management systems for EVs in China [31]. They compared and discussed energy consumption, daily travel distance, duration between two charging events, *etc.* But the vehicle uses were determined by the clustering algorithm, which resulted in a not very clear boundary between rental vehicles and personal vehicles. For the same vehicle use, Yuan Zou et al. analyzed 34 electric taxies (ETs) operating in urban areas and suburban districts based on the *Beijing Electric Vehicles Monitoring and Service Center*, including single-trip driving mileage, departure time, charging time, single-trip duration, charging duration, charging SOC [32]. To reduce the difficulty of massive data calculations, only 34 vehicles are extracted with a random sample approach from 1217 samples after the data cleaning and data filtering. Besides, the usage pattern of personal BEVs was also analyzed based on 41 users in [3]. Personal vehicles may have similar usage pattern characteristics when there is some difference in the size of the sample. Nevertheless, compared with personal use, the usage pattern of ETs showed some stochastic characteristics. With the increase of all-electric energy range (AER) of BEVs, limited sample size analysis may not reflect the total usage pattern of BEVs in the large-scale city enough.

All above, the limited sample size leads to a more significant influence of an individual on the results, which may not reflect the characteristics of fleets, especially for the big population cities such as predominantly the case in Beijing, China. With the development of EV technologies, the usage pattern of BEVs may also have some changes in recent years [25]. Therefore, this paper tries to give a comprehensive analysis of BEV usage patterns to provide valuable results to support a higher level of transportation electrification in Beijing, even in other metropolises with similar city scales. Compared with previous studies of usage pattern analysis (*e.g.* [3,32]), our contributions can be organized as follows:

For more comprehensive results, we analyze the usage pattern characteristics of 26,606 BEVs with 85 types of vehicle models, including 2,047,222 charging events and 8,382,032 travel events in Beijing, China, which are far more than previous studies (33,041 driving events and 4738 charging events in [3], and 775 driving events and 744 charging events in [21]). It is the first paper to analyze usage patterns of BEVs with such a large-scale amount of real-world data resources. Large-scale samples in the paper may reduce the individual bias with limited data resources and generate relatively robust results to reveal detailed characteristics. Therefore, some statistical results are provided with probability distribution function (PDF) rather than the IQR analysis or interval statistics used in [3,30,32]. We also verify and discuss the difference between the results of massive real-world data and the limited data resources.

This paper is organized as follows: Section 2 introduces the related works, including usage pattern analysis and associated applications by different motivations. Section 3 provides the data resource collection and presents the reasons to extract characteristics for the usage pattern analysis. Section 3 and Section IV argue the results of the charging pattern and travel pattern, respectively. The results of the previous studies are mainly compared and discussed. Finally, the last section presents the conclusions and future works that can be addressed based on the results of this work.

2. Data collection and characteristics establishment

2.1. Data collection

In this paper, we collect available data of 82,579 BEVs operating in Beijing from the open lab of National Big Data Alliance of New

Table 1
The critical information of the data resource.

Driving information	Battery information
Timestamp	SOC
Vehicle state	Pack voltage
Mileage	Pack current
Speed	Temperature
Longitude	
Latitude	

Energy Vehicles. Each vehicle has been pre-tagged with the use of the vehicle, including personal use, taxi use, and rental use. Rental use vehicles provide on-demand vehicle leasing services on an hourly or daily basis. Consumers can book vehicle rental hours according to their personal demands. The sampling period is from January 1, 2018, to December 31, 2018, with a maximum sample frequency of 0.1 Hz. In order to ensure the population is enough to analyze, we define that the days online must be more than 30 days, and the average daily travel distance must be more than 10 km. We finally extract 26,606 BEVs with enough data volume to analyze in this paper, including 2074 ETs, 5069 rental BEVs, and 18,707 personal BEVs. Eighty-five types of vehicle models are covered in the analysis. The AER of vehicles varies from 150 km to 416 km, and the battery capacity of vehicles ranges from 17 kWh to 82 kWh. The work of this paper is to compare the difference of the usage pattern of BEVs for different uses through data analysis, so the statistical time is limited to working days. Future studies will consider differences between workdays and weekends.

The critical information of the data resource is shown in Table 1. Moreover, only the longitude and latitude information of the public vehicles can be collected in the paper. According to the vehicle state, we finally extract 2,047,222 charging events and 8,382,032 travel events. Charging event can be recognized when the vehicle state is accessing to the grid for charging. Travel event is defined as a trip between two parking events with more than 30 min. The data segment processing method is proposed in our previous work [33].

2.2. Characteristics catalogues

Based on the previous and future focus, we establish some necessary characteristics that can better understand the travel pattern and charging pattern. Related characteristics and their definitions are provided in Table 2.

3. Charging pattern analysis

3.1. Time distribution

Previous studies assumed that the distribution of charging start time obeys a Gaussian distribution with a μ at 1:00 a.m. and a σ of 5, which neglected the fluctuation of the daily charging demand [17,34,35]. We describe the PDF of the charging time with a Gaussian mixture model (GMM) to estimate the charging demand of different time buckets accurately. The function is described as equation (1):

$$f(x) = \sum_{i=1}^{n} \left(A \times \frac{1}{\sqrt{2\pi}\sigma} e^{\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)}\right)_i \tag{1}$$

where μ is the mean of random variables subject to normal distribution; σ^2 is the variance of a random variable; i is the number of sub-distributions; and A is the amplitude of each distribution, because the sum of probability is 1. We apply the GMM model to realize the linear combination of different Gaussian distributions and realize the probability function approximation. In determining the number of peaks, we refer to the unsupervised learning clustering algorithm and preset the number of clusters (the number of sub-distributions) in advance; in the process of parameter solving, we use Expectation Maximum (EM) algorithm to estimate the parameters in GMM model.

We provide the charging time distribution with a blue hist from Figs. 1–3. The red line represents the total PDF of the distribution, and other dotted lines are the sub-distributions at different time buckets. The start time bucket is selected at the time bucket of the minimal charging demand, which can help us to build the GMM accurately. The parameters of the model are presented in the Appendix Table.A.1. Through the analysis, we find that:

(1) The distribution of personal BEVs is similar with the result of limited samples in [3]. There are two apparent charging peaks around 8:00 a.m. and 8:00 p.m. This situation is not changed with the EV technology development;
(2) The distribution of ETs from 2012 to 2014 has two peaks around 12:00 a.m. and 10:00 p.m., provided in [32]. However, we find an apparent extra charging peak at 3:00 p.m. in this research. It can be inferred that most taxi drivers would like to charge the vehicle before the evening peak to support the operation for next few hours. Furthermore, the AER of ETs collected in this paper (from 170 km to 300 km) is more than previous vehicles collected (130 km and 160 km). Longer AER results in a charging peak at noon dropped and shifted to around 3:00 p.m.;
(3) There are two charging peaks of rental BEVs around 4:00 p.m. and 11:00 p.m. Due to the uncertain and stochastic usage, the result does not have a similar trend with the morning and evening peaks. The minimum proportion is around 7:00 a.m. rather than 4:00 a.m. at the overnight, and the total distribution tend to be more uniform than the other two.

Table 2
Characteristics of the usage pattern.

Characteristics	Definitions
Charging time	The starting time bucket of the day when the electricity power flows from the gird to the vehicle (*hh*:*mm*).
Initial charging SOC	The percentage of remaining battery capacity before charging (%).
Availability	The probability of the charging opportunity (*hh*:*mm*).
Duration between charging	The duration between two adjacent charging events (*h*).
Spatial-temporal energy demand	Distribution of charging demand including grid load and charging energy in different districts.
First travel event start time	The time bucket of the day when the user starts the first travel event during a given day (*hh*:*mm*).
Final travel event finish time	The time bucket of the day when the user finishes the last travel during a given day (*hh*:*mm*).
The number of trips per day	The travel times of an EV during a given day.
Daily distance	The total distance travelled by a given EV during a given day (*km*).
Distance between charging	The distance travelled by an EV between two consecutive charging events (*km*).
Energy consumption	The required energy for travel one hundred kilometers of an EV (*kWh*/*km*).

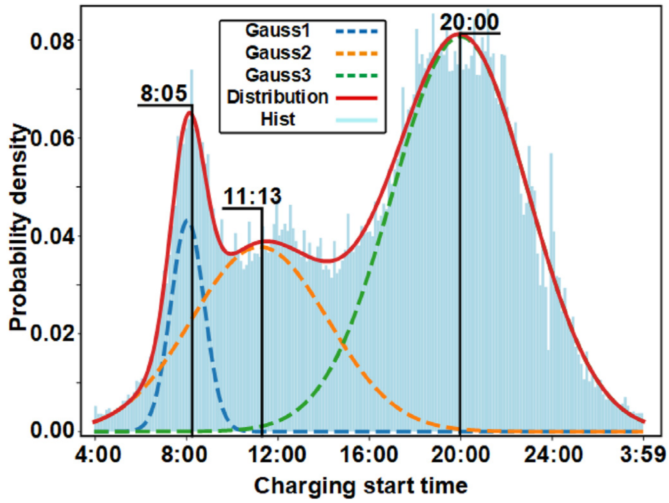

Fig. 1. Charging start time distribution of personal BEVs.

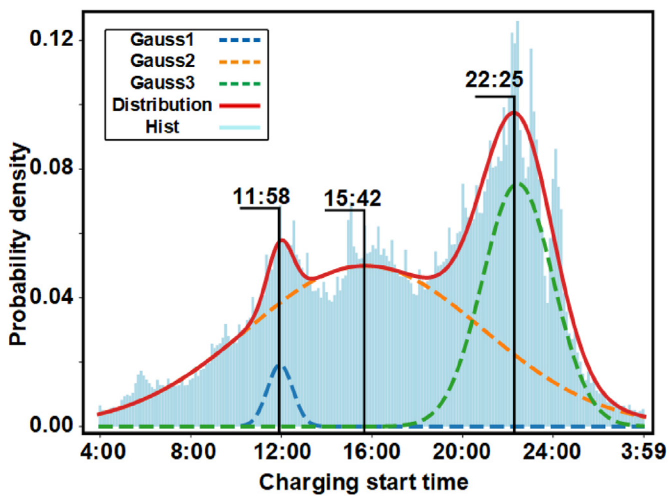

Fig. 2. Charging start time distribution of ETs.

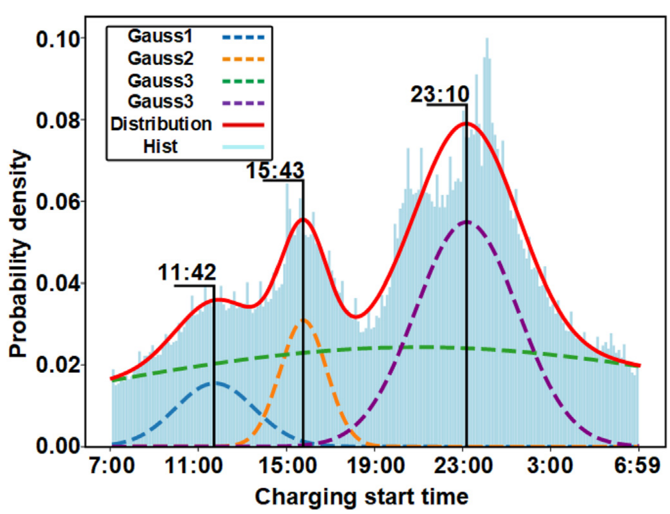

Fig. 3. Charging start time distribution of rental BEVs.

3.2. Initial SOC distribution

The purpose of initial SOC analysis of a charging event is to discover user habit and range anxiety. Fig. 4 presents the initial SOC distribution in different time buckets of the day. The blue, orange, and green distributions represent the results of personal BEVs, rental BEVs and ETs, respectively. We segment a day in 12 intervals to reduce the dimension of results. Moreover, to provide more detailed data support for other related studies, we provide the proportion of different SOC intervals at different periods in Appendix Table.A.2. When the data are hard to obtain, other researchers can use the results to determine the charging decision-making process or simulate the EV charging load. Through the analysis, we find that:

(1) The distribution of personal BEVs from 0:00 a.m. to 4:00 a.m. is located at the unclear SOC range (the orange box in Fig. 4). It can be suggested that there are few charging demands during these time buckets, which can also be verified from Fig. 1. The average values of distributions in other time buckets reduce from 50% SOC to 30% SOC over time (the red dotted line in Fig. 4);
(2) There is an apparent fluctuation of ETs at different time buckets of the day. From 0:00 a.m. to 8:00 a.m., the average charging initial SOC move from about 20% to about 60% and then gradually decrease to about 20% (the red arrows in Fig. 4). This finding can optimize the SOC threshold setting of the charging decision-making process;
(3) The time buckets of the day have little effect on the charging initial SOC of rental BEVs. The average charging initial SOC mainly less than the 40%. We infer that rental user only care about their own trips, not whether the next trip will satisfy other users. Therefore, the average is relatively low and range anxiety is transited to the rental service company.

3.3. Availability

The EV charging availability is the possible charging time buckets for EV users and is determined according to the parking status of vehicles. A parking event is defined as an event other than a charging event and a driving event. The vehicles are considered available for the grid integration operations when they are parked throughout the day [29]. Also, charging events can also be added into the availability calculation, because these time buckets are also available for charging vehicle. We finally make a statistic of the

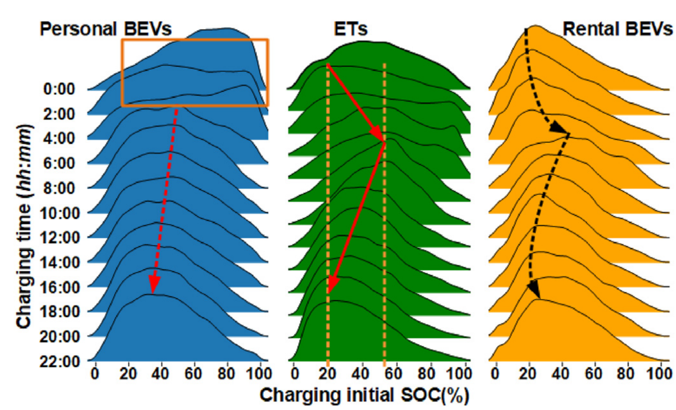

Fig. 4. Relationship between charging initial SOC distribution and charging time buckets of the day.

average proportion of non-traveling vehicles in different time buckets of different days such that to represent the opportunity to charge the vehicle.

When more charger construction in the future, more chance for BEV can charge the vehicle in most locations. The result can support the grid balance and provide scheduling potential. The figure below illustrates that:

(1) The trend of personal BEVs has high similarity with morning and evening peaks. This distribution indicates that the main usage purpose of personal BEVs is commuting in working days. The availability of daytime charging exceeds 90% (the red box in Fig. 5), indicating that personal BEVs have a large scheduling capacity of daytime charging behavior.

(2) The trend of ETs and personal BEVs are nearly similar before 8:00 a.m. and after 5:00 p.m., but the trend of remaining time buckets is the opposite. What is striking about the trend is the minimal average proportion of ETs. More than about 74.5% ETs can be charged during the daytime. Combined with the analysis about the daily distance, which is provided in section 4.3, it can be illustrated that as the average daily mileage of ETs is obviously less than that of ICEVs, some ET companies operate some ICEVs to ensure economic profits and operate some ETs to improve benefits of transportation electrification. Therefore, the low usage rate of ETs leads to high charging availability.

(3) The availability of rental BEVs shows a different trend from the others. The trend maintains at over 85% and can hardly reach 100% even at night. We can infer that this result may connect with the uncertain usage time buckets of rental BEVs.

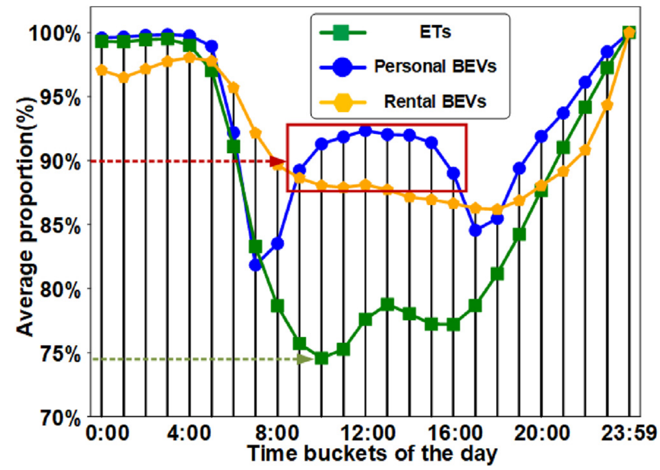

Fig. 5. Charging availability at different time buckets of the day.

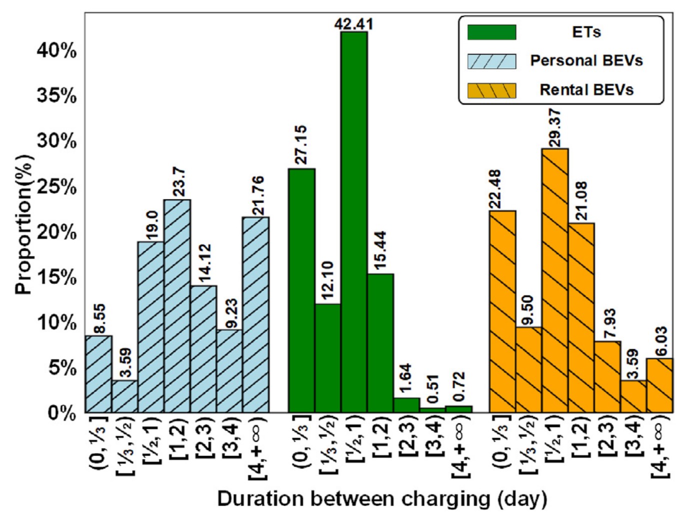

Fig. 6. The distribution of the duration between charging.

3.4. Duration between charging

Some works of literature assumed that vehicles will recharge three times a week [12] or once a day overnight [10,25]. Still, an increasing number of intended uses for EVs leads to a wide AER with a maximum of up to 500 km [11], which has already affected the habit of charging frequency. Fig. 6 shows the proportion of duration between two adjacent charging events in detail. As commercial vehicles, ETs are charged almost once a day or more, reaching a value above 80%. Rental BEVs also keep charging within about two days to ensure enough driving mileage. However, personal BEV peaks suggest that users often use the vehicle to keep charging once in about two days.

3.5. Spatio-temporal analysis of charging energy

Firstly, we analyze the charging power grid load from the relationship between time buckets of the day and charging energy consumption. The maximum and median of charging power grid load are two significant concerns in previous studies [17,25,34]. The maximum value can support a reference to limit range, and the median value represents a regular performance suggesting an overall impact of EV charging behavior on the power grid. We provide a statistical result in different time buckets of the day in Fig. 7. The figure below illustrates that:

Although there is a big gap in quantity among BEVs for different uses, the median value of charging grid load power can reach a similar level. From 10:00 p.m. to 6:00 a.m., the trend of ETs and personal BEVs is almost the same, but the impact of rental BEVs on the grid power in this time bucket is significantly higher than the other two, which may be caused by the high-power chargers. Due to ETs and rental BEVs belong to the commercial vehicle, they have a similar during the day from 6:00 a.m. to 7:00 p.m., while the trend of personal BEVs is more first and less later. During the remaining periods, at 7:00 p.m., the charging peaks as the ETs that are driven home and the rental BEVs that are returned start charging.

Secondly, different charging habits of EV users will lead to different distribution of power load in geographical space. Therefore, the difference of geospatial information of power load of public BEVs is analyzed and compared by the heatmaps, which are shown in Fig. 8 and Fig. 9. The areas surrounded by the green line are the urban districts in Beijing, including Xicheng, Dongcheng, Fengtai, Haidian, Chaoyang, Shijingshan. The areas surrounded by the orange line are the suburban districts in Beijing, including Yanqing, Huairou, Miyun, Pinggu, Shunyi, Tongzhou, Daxing, Fangshan, Mentougou and Changping. The closer the color is red in the figure, the higher the charging load density in the region is, and vice versa. The figure below illustrates that:

(1) The power load of ETs presents a wide distribution and high-density areas are scattered across the districts. The charging behavior of taxi has a certain relationship with its region. Especially for the suburban areas, the charging behavior has obvious regional aggregation, such as Huairou, Pinggu.

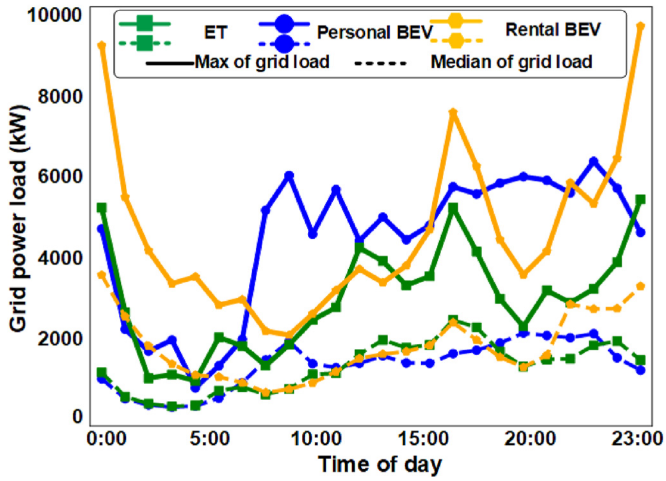

Fig. 7. Grid load generated by charging behaviors in different time buckets of the day.

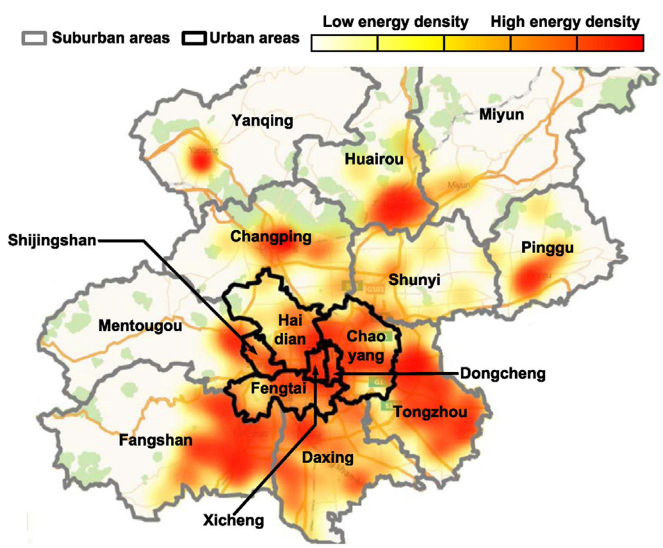

Fig. 8. Power load generated by charging behaviors of ETs.

(2) The power load distribution of rental BEVs presents a high concentration density at the urban areas. In the process of using the vehicle, the user generally needs to return the vehicle to the designated location. Most rental BEVs are charged by the company using its own charging facilities at these positions. As a result, the power load presents a very concentrated situation.

4. Travel pattern analysis

4.1. First travel event start time and final travel event finish time

The first travel event start time and the final travel event finish time are two important characteristics to establish EV usage simulation models, and they have been addressed in the previous studies [3,30,32]. However, only through a random sample from two independent distributions may result in a limited travel duration and travel time. Therefore, we focus on analyzing the independent distributions and linking the bridge between these two characteristics. To reduce the impact of overnight driving, 4 a.m. is treated as the daily statistical starting time. The results are shown

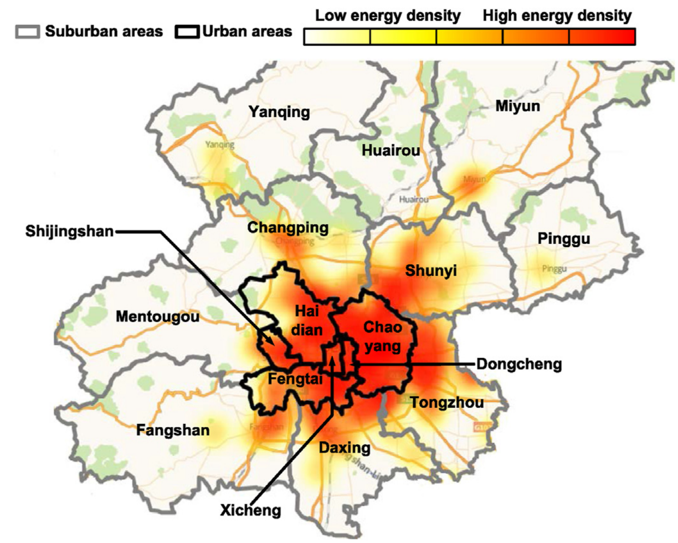

Fig. 9. Power load generated by charging behaviors of rental BEVs.

in Fig. 10, and the heat-map represents the two-dimensional characteristics distribution, where the darker the color is, the higher the probability is. A day has been divided into 24-time buckets of the day, the distributions are provided at the two edges, and the proportion of each time interval has been provided in Appendix Table.A.3.

It is within the expectation that a peak around 6:00 a.m. to 9:00 a.m. is observed in the distribution of first travel event start time as it coincides with the time people leaving home for work. The peak occurring at 5:00 p.m. to 7:00 p.m. in the final travel event finish time distribution of the personal BEVs when people arrive home

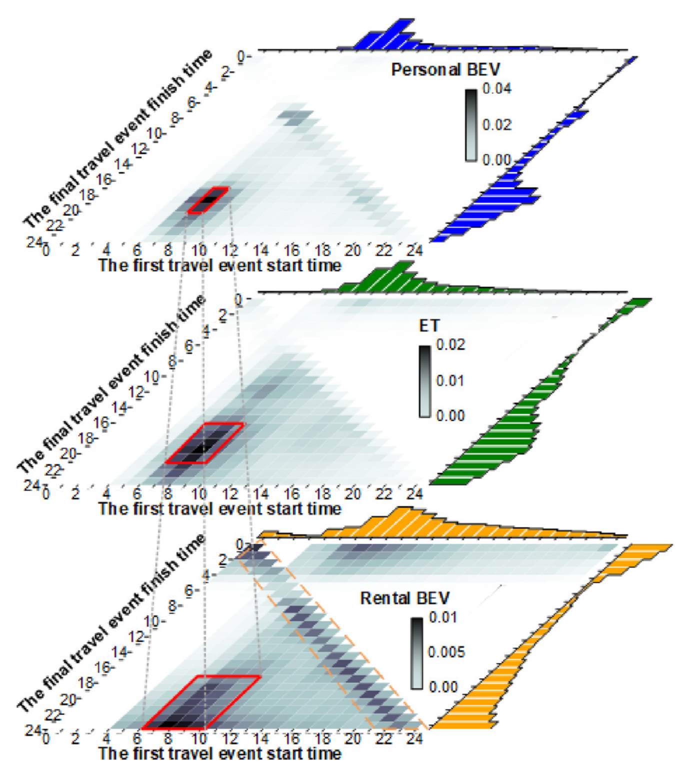

Fig. 10. The distribution of the first travel event start time and the final travel event finish time.

from work is also expected. The final travel event finish time of ETs is around 7:00 p.m. to 11:00 p.m. Rental BEVs have the latest final travel event finish time from 8:00 p.m. to 1:00 a.m. The concentration of travel patterns is gradually decreasing by personal BEVs, ETs, and rental BEVs, which is shown in the red box in the figure. Moreover, some short travel of rental uses may be caused by the shared car operating in the urban area.

4.2. The number of trips per day

When establishing an EV usage simulation model or trip chain model, people should know how many trips in the day. Therefore, we provide a statistical result of the number of trips per day in Fig. 11. It is not surprising that cases of 2 trips per day have the highest proportion, which can be explained by the fact that most personal drivers use BEV to commute between company and home. Moreover, the trends of ETs and rental BEVs are similar. More than twice trips per day are more than personal BEVs. The proportion is also illustrated clearly in the figure.

4.3. Daily distance

Daily distance reflects the range demand and range habits of an EV, which is concerned with the design of AER. As shown in Fig. 12, the distributions are generated by equation (1), and the parameters are provided in the Appendix Table.A.4. The average daily distance of personal BEVs is around 33 km, which can cover most daily commuting distances. ET has a 128.93 km average daily distance, which is a little higher than that in [32] (117 km per day) but still far lower than the traditional taxis [31] (more than 250 km per day). We infer that this increase in daily distance is also caused by the improvement of the driving range capability of an EV in recent years. Moreover, there are two rental BEV peaks around 43.2 km and 155.93 km, which may be caused by the different travel purposes.

4.4. Distance between charging

The daily distance can only represent the range demand of users without the charging habits. However, the distance between charging can reflect the range anxiety and travel habits of users,

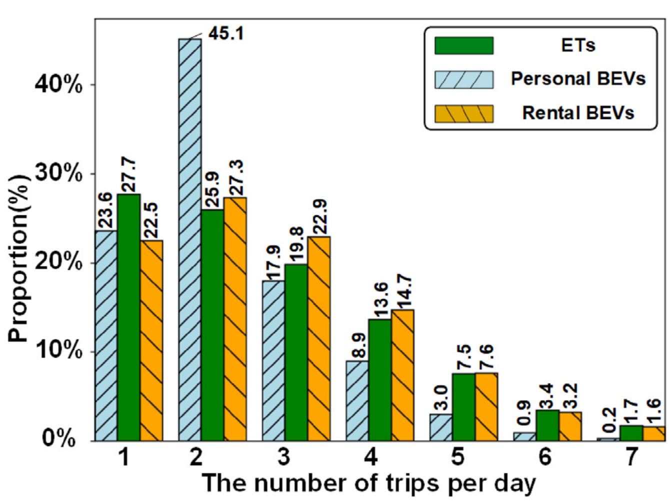

Fig. 11. The result of the number of trips per day.

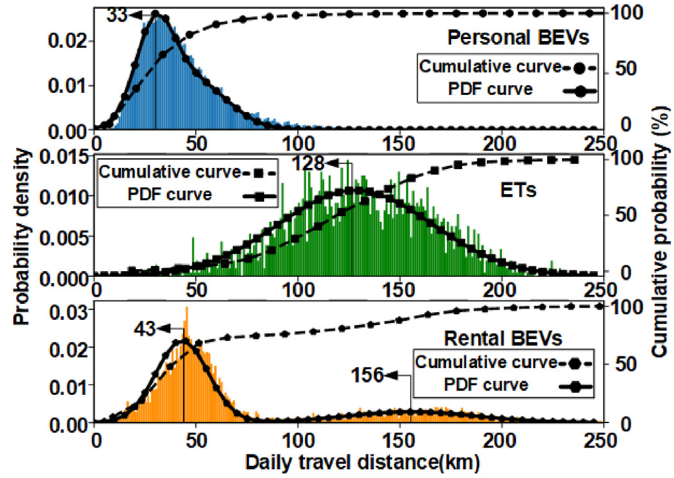

Fig. 12. Daily travel distance distribution.

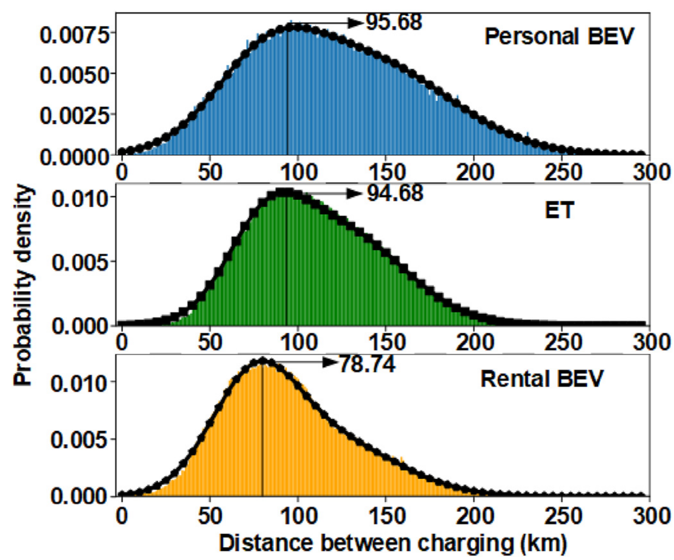

Fig. 13. Distance between charging distribution.

and combining with the charging frequency can also support the analysis of city mobility. The distributions of the distance between charging are shown in Fig. 13. Compared with the result in [3], which is concentrated on the 40 km–60 km, the distance between charging of personal BEVs has already grown to 95.68 km. The average value of ETs is around 94.68 km, which reaches two-thirds of its average daily distance. The AER of ETs still cannot provide enough support for daily operation and range anxiety. Rental BEV has the lowest average value because of its operating mode, which has to full charge at the beginning of each service. The parameters are provided in the Appendix Table.A.4.

4.5. Energy consumption

Energy consumption (EC) per 100 km of one vehicle model has been calculated and compared in Fig. 14. Due to the sampling frequency limitation, we apply ΔSOC, battery capacity, and travel distance to calculate the energy consumption per 100 km. The total travel distance of personal BEVs has reached 7 million kilometers,

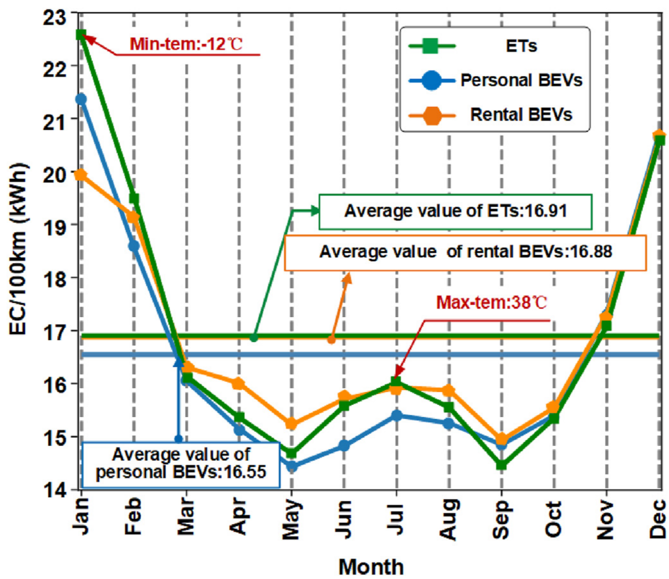

Fig. 14. EC/100 km in different months.

and the mileage of rental BEVs and ETs has reached more than 5 million kilometers, respectively. Compared with the related study [31], it has shown some different conclusions. The EC/100 km of the personal BEVs doesn't show an apparent higher value than others. On the contrary, the average of the EC/100 km of the personal BEV is the lowest. In the high-temperature summer (June–August) and low-temperature winter (December–February), the EC/100 km of ETs is relatively high. In other periods, the EC/100 km of rental BEVs is relatively high. There are mainly caused by the following reasons:

On the one hand, the AER of the ETs and personal BEVs are not the same in [31], which may result in inconsistent horizon. On the other hand, personal BEV users may use the heating, ventilation, and air conditioning systems more often or more aggressively. However, based on the analysis of travel time and travel distance, most personal use is for commuting. Therefore, in terms of summer, the temperature of different commuting time buckets is relatively lower than the temperature during the taxi usage period, which may result in a lower EC/100 km of the personal BEVs. Besides, the EC/100 km in the winter of these BEVs are all higher than the other months and almost the same. Because the temperature during winter travel by personal BEVs is low and the demand for heating, ventilation, and air conditioning systems is great, it is not much different from ETs and rental BEVs.

5. Conclusion and future work

The development of information technology promotes massive real-world data application in the field of EV. The paper has applied 26,606 BEVs operating in Beijing, China, in 2018, whose data volume is far more than the previous research to analyze the usage pattern of personal BEVs, ETs, and rental BEVs. According to the need of the transportation and grid, ten usage pattern characteristics have been calculated in a detailed approach, including PDF or proportion. The paper results can support many valuable prior distributions for a higher level of transportation electrification in Beijing, even in other metropolises with similar city scales. More importantly, different from the previous studies, some characteristics have been established concerning each other, so that the statistical results are not just independent distributions. The detailed results have greatly supported the establishment of the real-time simulation model and can better reflect real operating environment of BEVs.

Future work mainly includes the behavior model and simulation model establishment based on the results of this paper. Also, to establish environmental parameters for the vehicle scheduling issues, battery charging scheduling, and grid load forecast.

CRediT authorship contribution statement

Dingsong Cui: Writing – original draft, Writing – review & editing, Investigation. **Zhenpo Wang:** Supervision, Conceptualization. **Peng Liu:** Supervision, Funding acquisition. **Shuo Wang:** Investigation, Writing – review & editing. **Zhaosheng Zhang:** Investigation, Writing – original draft. **David G. Dorrell:** Writing – review & editing. **Xiaohui Li:** Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table.A.1
Parameters of time distribution

Uses	No.	A	μ	σ
Personal	1	0.079	8.08	0.735
	2	0.282	11.23	2.98
	3	0.599	20.00	2.96
Taxi	1	0.027	7.97	0.56
	2	0.647	11.71	5.637
	3	0.294	18.42	1.553
Rental	1	0.070	4.69	1.798
	2	0.082	8.72	1.059
	3	0.943	13.94	15.455
	4	0.322	16.16	2.340

Table.A.2
The proportion of different SOC intervals in different time buckets.

	Time buckets	Battery SOC intervals									
		[0,10)	[10,20)	[20,30)	[30,40)	[40,50)	[50,60)	[60,70)	[70,80)	[80,90)	[90,100)
Personal BEVs	[0,2)	2	4.4	6.3	8.5	11.2	12.4	14.4	14.7	14.5	11.6
	[2,4)	5	8.4	9.9	11.2	11.9	11.5	10.6	10.5	10.4	10.6
	[4,6)	4.5	8	9	9.4	10	10.8	10.4	11.1	12.5	14.4
	[6,8)	3.7	9.9	12.8	12.9	13.9	13.3	11	9.2	7.8	5.5
	[8,12)	3.4	9.6	13.7	14.7	15.3	14.2	11.8	9.6	5.8	1.9
	[12,14)	4	10.2	13.4	14.4	14.7	13.6	11.3	9.2	6.3	2.8
	[14,16)	3.8	10.4	13.2	14	14.6	13.7	11.3	9.3	6.3	3.4
	[16,18)	4.1	10.5	13.6	14.7	14.7	13	10.5	9.1	6.4	3.5
	[18,20)	4.4	10.8	14.1	15.4	14.9	13.3	10.8	8.2	5.4	2.9
	[20,22)	3.8	11.6	15.3	16	15.5	13.5	10.4	7.8	4.4	1.7
	[22,24)	2	4.4	6.3	8.5	11.2	12.4	14.4	14.7	14.5	11.6
ETs	[0,2)	3.3	7.4	9.3	12.7	14.2	14.2	13.8	11.4	8.9	4.8
	[2,4)	8.5	13.6	13.3	13.2	12.1	11.2	9.6	7.8	6.6	4.2
	[4,6)	7.2	11.1	11.6	12.4	11.4	9.8	10	8.8	8.9	8.9
	[6,8)	3.4	7.8	10.3	13.8	14.4	14.6	11.9	9	7.5	7.4
	[8,12)	4.1	7.5	10.6	12.3	13.7	13.9	11.9	9.9	9.5	6.5
	[12,14)	2.4	6.2	10	13.8	16.7	19.1	13.7	10.2	5.9	2.1
	[14,16)	1.8	5.7	10.8	15.7	17.8	18.5	14.4	9.8	4.1	1.4
	[16,18)	3.3	10.5	16.5	17.8	17.2	14.9	9.4	6	3.2	1
	[18,20)	4	11.5	16.5	18.7	17.7	13.8	8.2	5.6	3	1
	[20,22)	5.1	13.6	17.1	16.9	15.3	13.1	8.3	5.8	3.6	1.3
	[22,24)	3.3	7.4	9.3	12.7	14.2	14.2	13.8	11.4	8.9	4.8
Rental BEVs	[0,2)	7.7	15.3	18.6	16.1	13.7	10.8	7.5	5.6	3.6	1.2
	[2,4)	9.2	17	18.4	15.8	12.8	10	7.9	5	2.8	1.2
	[4,6)	9.2	15.9	17.7	15	13	10.4	8	5.6	3.5	1.6
	[6,8)	6.9	14.4	15.3	14.3	13.6	11.9	8.6	6.8	5.7	2.6
	[8,12)	4.8	10.5	13	13.6	14.7	14.5	10.6	9.3	6.6	2.4
	[12,14)	4.5	10.5	15.6	16.8	16.2	14.2	10	6.7	4.1	1.3
	[14,16)	4.5	11.5	17.4	18.1	16.5	13.2	8.2	5.7	3.6	1.3
	[16,18)	5.5	14.1	19.6	17.3	14.5	11.5	7.3	5.4	3.5	1.2
	[18,20)	4.8	12.5	17.6	17.4	16.2	13	8.1	5.8	3.4	1.2
	[20,22)	5.1	12.7	17.2	16.6	15.4	12.8	8.6	6.4	3.9	1.3
	[22,24)	7.7	15.3	18.6	16.1	13.7	10.8	7.5	5.6	3.6	1.2

Table.A.3
The proportion of first travel event start time and final travel event finish time.

Time	First travel event start time Proportion			Final travel event finish time		
	Personal	Taxi	Rental	Personal	Taxi	Rental
[0,1)	0.3	0.5	2.3	1.2	3.3	7.6
[1,2)	0.1	0.2	1.5	0.7	2.0	6.6
[2,3)	0.1	0.1	1.0	0.4	1.1	5.2
[3,4)	0.1	0.2	0.7	0.2	0.8	4.3
[4,5)	0.4	2.0	3.3	0.1	0.4	1.8
[5,6)	2.2	6.0	3.9	0.1	0.3	0.6
[6,7)	16.4	16.8	8.0	0.7	0.4	0.5
[7,8)	28.1	21.6	11.8	3.8	0.7	1.0
[8,9)	15.5	13.8	10.9	3.1	1.2	1.5
[9,10)	8.7	9.5	9.2	1.8	2.0	1.6
[10,11)	5.3	7.0	7.3	1.9	2.9	1.8
[11,12)	3.6	4.8	5.9	2.4	3.8	2.2
[12,13)	3.1	4.1	5.2	2.5	3.9	2.3
[13,14)	3.2	4.1	5.1	2.6	3.4	2.5
[14,15)	2.7	3.4	4.7	3.0	4.3	3.0
[15,16)	2.5	2.8	4.0	4.1	5.8	3.9
[16,17)	2.7	2.3	3.7	6.5	7.6	4.7
[17,18)	3.1	1.6	3.4	12.4	8.8	5.2
[18,19)	2.2	1.1	3.1	15.5	9.7	6.0
[19,20)	1.6	0.9	2.5	12.6	10.5	6.7
[20,21)	1.2	0.6	2.3	10.2	9.5	7.2
[21,22)	0.8	0.4	2.1	8.8	8.3	7.8
[22,23)	0.4	0.3	1.5	6.3	7.5	9.3
[23,24)	0.2	0.1	1.0	3.3	6.3	11.1

Table.A.4
The parameters of daily distance distribution.

Uses	No.	A	μ	σ
Personal	1	0.48	29.57	18.8
	2	0.46	48.54	33.22
Taxi	1	1.01	128.93	37.76
Rental	1	0.70	43.20	13.00
	2	0.23	155.63	32.62

Table.A.5
The parameters of distance between charging distribution.

Uses	No.	A	μ	σ
Personal	1	0.35	81.64	60.55
	2	0.67	139.36	94.11
Taxi	1	0.33	81.40	44.22
	2	0.67	123.43	73.11
Rental	1	0.59	75.17	49.50
	2	0.42	120.71	73.70

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