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Seasonal Effects on Electric Vehicle Energy Consumption and Driving Range: A Case Study on Personal, Taxi, and Ridesharing Vehicles

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Abstract

The variation in BEV energy consumption and driving range under different weather and driving conditions can affect the usefulness and consumer acceptance of these vehicles. Thus, there is a need to better understand and quantify seasonal factors that affect consumption and range under real-world driving conditions. In this paper, a dataset representing the real-world driving activity of 197 BEVs of the same model recorded over 12 months at a polling frequency of 0.1 Hz is analyzed to estimate BEV performance across different driving applications (personal driving, taxi operation, and ridesharing) and seasons (spring/autumn, summer, and winter). The results show that the electricity consumption, travel patterns, and charging patterns of BEVs vary significantly by both vehicle application and season. For example, BEV models with a range of 160 km, recharged every 1.6 days on average, can meet most trip demands of personal vehicles. However, the same BEV model when used for ridesharing or taxi purposes, is driven much more and recharged more frequently. The results also show that actual BEV electricity consumption (EC) differs significantly from the consumption predicted by the New European Driving Cycle (NEDC) test, with real-world EC being 7%–10% higher than predicted by the NEDC test cycle. Furthermore, the real-world range of personal-use BEVs in winter is only 64% of the NEDC-estimated range. The study found that, when the ambient temperature is lower than 10°C, electricity consumption increases 2.4 kWh/100 km for every 5°C decrease in temperature. When it is higher than 28°C, EC increases 2.3 kWh/100 km for every 5°C increase in temperature. These findings imply that manufacturers should design BEVs with application-appropriate driving ranges and make R&D investments for improving battery performance in cold environments.

Keywords

BEV, energy consumption, travel patterns, charging patterns, seasonal variation, vehicle applications

1. Introduction

The global electric vehicle market is developing rapidly, with annual sales exceeding 1.2 million and stock surpassing 3 million in 2017 (International Energy Agency, 2018). This is especially true in China, where the annual production of battery electric vehicles (BEVs) has surged, mainly due to policy incentives, from 39,000 vehicles in 2014 to 790,000 vehicles in 2018 (Wang, 2017; Ou et al., 2019). Passenger BEVs in China are used largely as personal, fleet (including ridesharing vehicles), and taxi vehicles, accounting for about 47%, 41% and 12%, respectively, of the 302,000 new passenger BEVs in 2016 (CATARC, 2017).

The BEV demand in China is concentrated primarily in large cities, due to higher personal incomes and strong local policy incentives. For example, in Beijing the annual sales of BEVs increased significantly over the past three years—from 49,000 in 2016 to 73,000 in 2018—making Beijing the largest BEV market among Chinese cities. Due to the growing demand for BEVs, Beijing has established an annual BEV sales maximum quota (Yicai, 2017).

The growing ownership of BEVs comes with concerns about battery safety, vehicle quality, and driving range (range anxiety). Reduced and uncertain ranges are fundamentally associated with increased and varying on-road energy consumption of BEVs. This study aims to improve understanding of the extent of and reasons for the variation in BEV real-world energy consumption and driving range.

Variation in BEV energy consumption and driving range may be caused by different driving applications (e.g. personal use, shared mobility and taxi) that are associated with different driving intensities and patterns. Some BEV owners have joined Didi, a Transportation Network Company (TNCs) in China similar to Uber and Lyft in the U.S. As of 2017, Didi had more than 200,000 registered BEVs and plug-in hybrid electric vehicles (PHEVs) on its platform in more than 20 cities across China (China News Service, 2017; Schlobach and Retzer, 2018).

Commuting is the most common travel type for personal vehicles. In China, a one-way commuting trip is usually less than 30 km, with regular and fixed patterns during weekdays (Beijing Transport Institute 2019). However, the annual driving distances for taxis and ridesharing vehicles can reach 80,000 to 100,000 km (about 200 to 300 km each day), varying largely due to factors such as weather and travel demands (Beijing Transport Institute, 2019). A similar pattern is observed in the United States. Twenty percent (20%) of taxi and ridesharing vehicle-days are associated with a daily driving distance over 200 miles, while less than 1% of vehicle-days for personal drivers reach this distance (Moniot et al., 2019). The travel pattern differences by vehicle application may result in different fuel consumption and different needs for BEV ranges.

Weather and driving conditions may also affect BEV energy consumption, which has implications on consumer acceptance, battery sizing, and the environmental impacts of BEVs. Dong et al. quantified the impact of reliable range estimation on BEV feasibility, which further illustrates the importance to estimate the weather impacts on BEV energy consumption (Dong et al., 2019). As with conventional vehicles, standard test cycles, such as the New European Driving Cycle (NEDC) adopted in Europe and China, are still being used to estimate energy consumption and driving range. While these test cycles are useful for comparing vehicles, it is widely accepted that they do not reflect real-world driving (De Cauwer et al., 2015; He et al., 2018). Actual energy consumption can be 29.3% to 37.5% higher than NEDC test results for internal combustion engine vehicles (ICEVs) (Ma et al., 2019).

The goal of the study is to better estimate BEV real-world energy consumption and driving ranges. More accurate estimates of real-world energy consumption and range can potentially reduce consumer anxiety and promote consumer acceptance. They can also help manufacturers optimize BEV range for personal consumers and taxi companies and can lead to better assessments of the environmental benefits of BEV adoption.

The existing literature on BEV energy consumption and range does not consider variations in travel patterns and electricity consumption by vehicle application and season. A detailed literature review is described in Section 2.

This study uses using large-scale, real-world driving data to examine the influence of temperature on real-world BEV electricity consumption and driving range for different vehicle applications. It uses operation data from 197 vehicles of China's best-selling BEV model operating in Beijing. Vehicles are classified as (1) personal vehicles, (2) taxis, or (3) ridesharing vehicles, using the *k*-means clustering method. Travel and charging patterns for different vehicle applications in different seasons are then derived. Electricity consumption and driving range are then analyzed and compared across vehicle application, season, and ambient temperature.

Based on a thorough literature review, we believe this to be the first paper to use real-world BEV driving data to illustrate the operational and electricity consumption differences among personal vehicles, taxis, and ridesharing vehicles in China as far as we know. The results show that electricity consumption, travel patterns, and charging patterns vary significantly by application and season. The findings imply that the manufacturers and the government should (1) promote BEVs with ranges appropriate for their intended applications to minimize total ownership cost and (2) increase investment into battery performance improvements in cold environments.

The remainder of the paper is structured as follows: Section 2 is a literature review of the travel patterns and energy consumption of BEVs. Section 3 introduces the data and methods used for data processing. Section 4 describes the results of travel and charging patterns and discusses the effects of vehicle application and season on electricity consumption and range. The last section discusses limitations, future research, and conclusions, including implications.

2. Literature Review

The number of studies examining BEV travel patterns using real-world driving data have gradually increased since 2013, especially for personal vehicles and taxis. The travel patterns of personal vehicles have been studied in detail around the world—such as in the U.S. (Nicholas and Tal, 2016), Greater Stockholm in Sweden (Jakobsson et al., 2016), Australia (Speidel and Bräunl, 2014), and England (Quirós-Tortós et al., 2015).

De Cauwer et al. (2015) used vehicle data from the Flanders Living Lab Electric Vehicles program to classify vehicles into pool vehicles and personal vehicles, based on average vehicle driving distance, and studied the mileage distribution of each. Researchers at Idaho National Laboratory (INL) studied a much larger sample of vehicles. They gathered on-road vehicle operation data from 21,600 personal vehicles to study the real-world travel distance distribution of BEVs (Shawn et al., 2014). For taxis, Zou et al. (2016) used battery electric taxi data from the Beijing Electric Vehicles Monitoring and Service Center (BEVMSC) and analyzed the travel distance distribution and seasonal variation in charging characteristics of BEVs. The travel patterns of taxis in New York City have been analyzed to optimize BEV feasibility (Hu et al., 2018). Moniot et al. (2019) compared the travel patterns of personal vehicles, taxis in Columbus, Ohio, and ride-hailing vehicles in Austin, Texas, to determine the importance of charging infrastructure. That study compared the three vehicle applications but focused on conventional vehicles rather than BEVs. The data sources and main findings in the literature are listed in Table 1. Thus, there is no research, at least in China, comparing different BEV applications (personal use, taxi operation, and ridesharing) based on large BEV driving datasets.

Table 1. Travel pattern research literature

Author	Powertrains	Data acquisition	Vehicle number and type	Location	Travel pattern
(Zhang and Wang, 2014)	ICEV	Trajectory data	112 personal vehicles	Beijing, China	39km/day
(Shawn et al., 2014)	BEV	Monthly travel data	21,600 personal vehicles	U.S.	42.09–42.76 km/day
(De Cauwer et al., 2015)	BEV	Trajectory data	120 pool vehicles	Europe	11.54km/day
	BEV	Trajectory data	100 personal vehicles	Europe	19.04km/day
(Zou et al., 2016)	BEV	Trajectory data	34 taxis	Beijing, China	118km/day
(Hai, 2017)	ICEV	Investigation	Personal vehicles	Six cities in China	Beijing: 33.9km/day
	BEV	Investigation	Personal vehicles	Six cities in China	Beijing: 34.5km/day Charging frequency 2.7–4.8 times per week.
(Hu et al., 2018)	ICEV	Trip data	14,144 yellow taxis	New York City	270km/day
(Moniot et al., 2019)	ICEV	Trip data	5,000 drivers ride hailing	Austin, Texas	142 km/day
	ICEV	Trajectory data	Personal vehicles	Columbus, Ohio	Less than 1% of vehicle-days exceeded 200 miles (322km) of driving in a day.
	ICEV	Trajectory data	146 taxis	Columbus, Ohio	250-mile-range EV can meet 95.7% of taxi travel needs with overnight and public charging infrastructure. 100-mile range can meet only 34.4% of taxi travel days needed.

The relationship between real-world electricity consumption and driving range and relevant factors have been analyzed by a few studies. Road grade (Hu et al., 2012; Wang et al., 2008), traffic congestion (Brundell-Freij and Ericsson, 2005), driving on freeways or local roads (Fetene et al., 2017; Heide and Mohazzabi, 2013), and weather have been analyzed regarding their effect on real-world electricity consumption. In these studies, researchers typically used onboard BEV operational data, which is high in polling frequency but collected from a small number of vehicles. Reyes et al. (2016) performed an experiment in Canada with a Toyota Leaf and a Mitsubishi i-MiEV to determine the sensitivity of electricity consumption to ambient temperature. However, that study was based on only three vehicles. Big data, such as vehicle trajectory data, makes it possible to comprehensively analyze the factors affecting energy consumption. In Denmark, fuel consumption in winter was found to be 30% higher than in summer according to Fetene et al. (2017). Similar research to determine the effect of extremely cold temperatures has been carried out in Quebec, Canada (Zahabi et al., 2014). The variation in EC isn't significant for mild temperatures (13℃–16℃) (Birrell et al., 2014). However, most of the studies focus on a single application, such as personal vehicles.

In summary, little research has been aimed at determining the different travel patterns among different vehicle applications, such as personal use and ridesharing, especially using big data from China. While travel patterns and energy consumption might vary significantly across different applications in different ambient temperatures, there is insufficient research to quantify or verify it.

3. Data and Methods

3.1. Data Overview

This study uses data obtained through the remote vehicle monitoring process that adheres to *Technical specifications of remote service and management system for electric vehicles,* published in 2016 (Ministry of Industry and Information Technology, 2016). The data fields include intended vehicle use, GPS information, speed, travel distance, and the state of charge (SOC) of the battery, as shown in Table 2. The data is collected at a polling frequency of 0.1 Hz.

Table 2. Data sample

Vehicle	Intended	Acquisition	Location	Speed	Cumulative	SOC

number	vehicle use	time	Latitude	Longitude	(km/h)	distance (km)	(%)
1	taxi	2014/5/6 7:52:41 AM	31.16	121.14	70	99	80.0

The data sample covers a total of 197 BEVs: 119 registered as personal vehicles and 78 registered as taxis. Registered intended use categories in the data don't include ridesharing. The data covers a total of 41,660 car-days, from January 2015 to February 2016, with a total distance of 4,401,000 kilometers. Data for vehicles registered as taxis are distributed across the Daxing District in southern Beijing, as illustrated by their charging locations in Figure 1. The charging locations are defined as the stop locations of each vehicle after travelling. Note that the locations may not be actual charging locations, they are depicted on the map to show the spatial distribution district of travelling. The vehicle model used as a taxi has a battery capacity of 30.4 kWh and a nominal driving range of 200 km (NEDC test), as shown in the second column of Table 3. Personal BEV charging places are located all around Beijing (Figure 1). These vehicles are the same model (also the EC-series body) with a smaller battery capacity of 25.6 kWh and a nominal driving range of 160 km (NEDC test). Attributes of the personal-use and taxi models in this study are also shown in Table 3.

Table 3. Vehicle attributes for the taxi and personal vehicle models used in this study

Attribute	Registered Usage	
	Taxi	Personal
Size (length, width, height), mm	4,025 × 1,720 × 1,503	
Curb weight, kg	1,295	
Charging	Level 1：220–230 V, 3.3kW Level 2：330 V, 37kW	
Size	A0, sedan	A0, sedan
Motor	TZ30S01	TZ20S02
Motor maximum power, kW	53	45
Battery type	$Li(NiCoMn)O_2$ (NCM)	$LiFePO_4$ (LFP)
Battery capacity, kWh	30.4	25.6

NEDC range, km	200	160
NEDC energy consumption, kWh/100 km	15.2	16

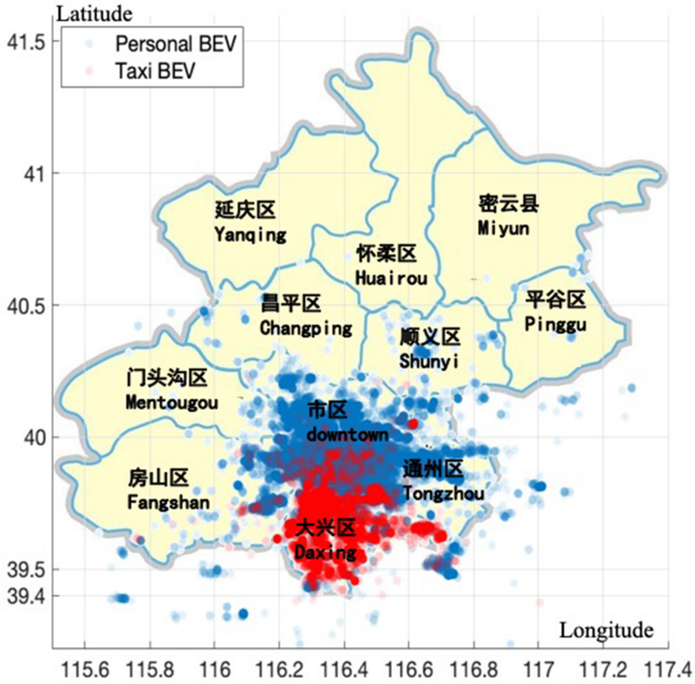


Figure 1. Taxi and personal BEVs charging locations distributed across Beijing
The red color indicates the taxis distributed across Daxing District, and the blue color indicates the personal BEVs distributed across Beijing. The points are drawn with 10% transparency. Where the color is darker, the frequency is higher.

3.2. Data Processing

The data exported from the monitoring platform is processed and segmented into the daily vehicle-kilometers-traveled (DVKT) distribution for each car. The data processing is then finished with Matlab (ver. R2018b) by Mathworks®. Data processing includes the following steps:

1. Normalize data format. The data format is unified and adjusted according to the time sequence to correct any changes in data sequencing that may occur during data transmission.
2. Clean data. There may be missing points because of losses during data transmission or because of data overflow. The missing points are smoothed.

3. Segment trips. The data is segmented—any two adjacent data points with a stop longer than 30 minutes are cut into two trips.

4. Delete outlier trips. Because the speed limit on expressways in China is 120 kph and statutory provisions limit continuous driving to 4 hours (State Council, 2004), single trips longer than 480 km are not allowed. To include complete data as much as possible, trips longer than 960 km (double the criteria) are deleted. At the same time, trips lasting less than 5 minutes or 1 km are omitted to avoid data deviation.

5. Derive DVKT. Trips with the same departure date are defined as trips on the same day. Distances driven by the same vehicle on the same day are accumulated as DVKT.

6. Define charging events. Charging events are not directly recorded and are therefore defined based on changes in the SOC. A charging event is defined when the starting SOC of a new trip is 10 percentage points higher than the arrival SOC of the prior trip and the time interval between these two trips is within 24 hours. The time limit aims to avoid data loss.

7. Identify ridesharing vehicles. The personal vehicle data records include both ridesharing and exclusive personal use and need to be separated. This is discussed in Section 3.3.

8. Fit gamma distribution. The DVKT results from Step 5 are used to fit the gamma distribution for more convenience in mathematical derivation and discussion of travel patterns. A more detailed explanation is provided in Section 3.4.

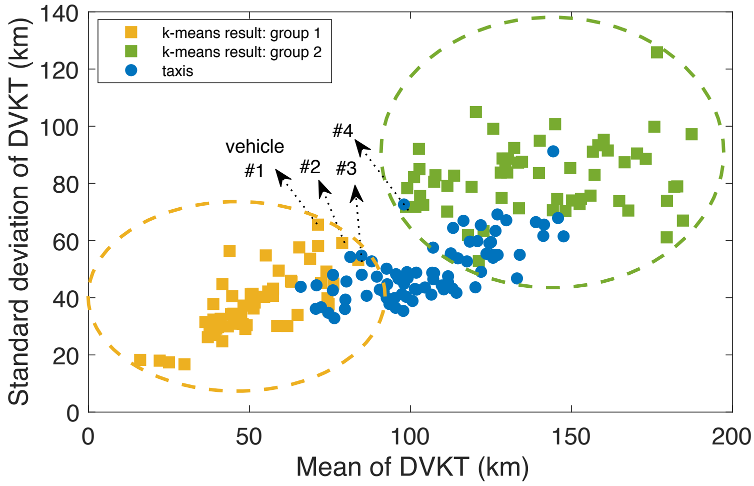
9. Calculate electricity consumption and range. SOC is used to calculate cumulative energy consumption and range during a trip (further explained in Section 3.5).

3.3. Vehicle Application Separation with *k*-means

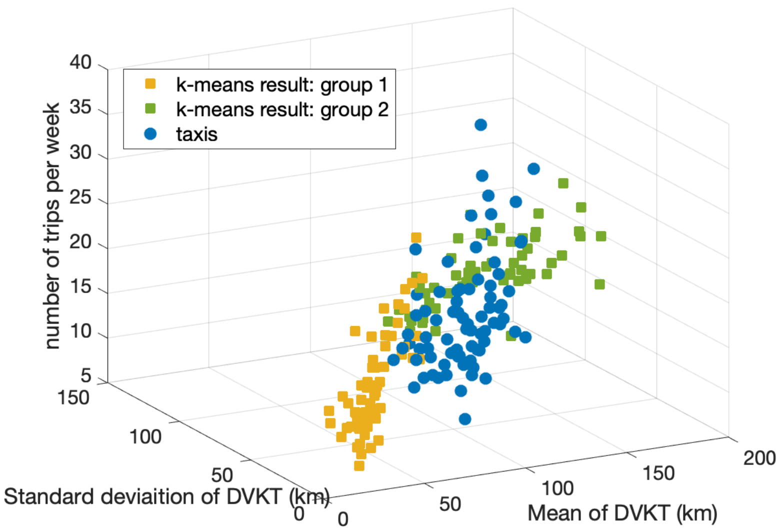
Registered personal vehicles are not separated into ridesharing and exclusive personal-use vehicles in the dataset. Therefore, the *k*-means clustering method is used to separate the two. For *k*-means clustering, the squared Euclidean distance is the most commonly used method (Fotouhi and Montazeri-Gh, 2013) and is adopted for driving pattern identification (Li et al., 2019). It is also adopted here, with the 2-dimensional

Euclidean vector consisting of the mean and the standard deviation of DVKT. The mean DVKT indicates the average distance traveled by the driver, and the standard deviation of DVKT indicates the variation of each day's trips. The most striking difference between ridesharing and personal vehicle operation is the greater utilization, or higher DVKT, of ridesharing vehicles (Moniot et al., 2019). Also, the standard deviation in DVKT of taxis and ridesharing vehicles can reach more than 50 km (Chaudhari et al., 2016), while it is only 38 km on average for personal vehicles in Beijing (Hou et al., 2013). The clustering results are shown in Figure 2 (a). The clustering is validated by a 3-dimensional k-means clustering adding the number of trips per week as another clustering parameter. It turns out the result is exactly the same as the 2-dimensional clustering result shown in Figure 2 (b).

(a)


k-means result: group 1
k-means result: group 2
taxis
vehicle
#1
#2
#3
#4
Standard deviation of DVKT (km)
Mean of DVKT (km)
0
20
40
60
80
100
120
140
0
50
100
150
200

(b)


k-means result: group 1
k-means result: group 2
taxis
number of trips per week
5
10
15
20
25
30
35
40
Standard deviaition of DVKT (km)
0
50
100
150
Mean of DVKT (km)
0
50
100
150
200

(c)

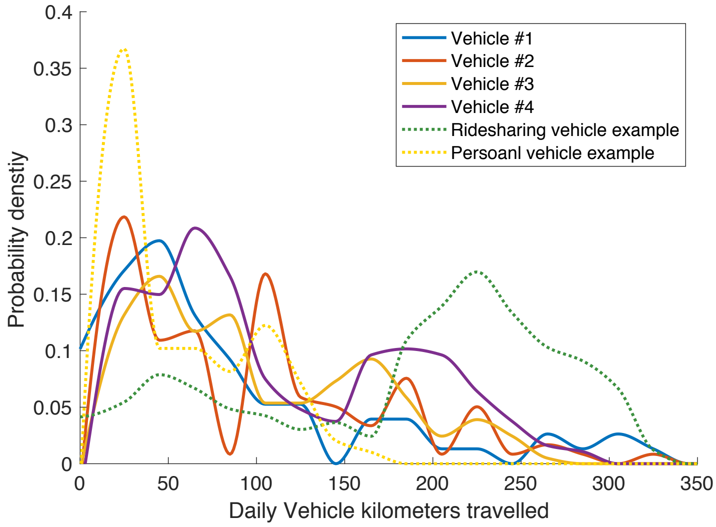


Figure 2. Results of *k*-means clustering. (a) 2-dimensional clustering; (b) 3-dimensional clustering; (c) DVKT distribution of the points on the boundary.

In (a) and (b), yellow squares with smaller means, smaller standard deviations and smaller number of trips per week indicate shorter and more regular distances traveled, which is often the sign of commute trips for personal use. Green squares with larger means, larger standard deviations and larger number of trips per week indicate ridesharing vehicles. Blue points indicate taxis. Each square/circle represents a car's average travel pattern. In (c), the solid lines refers to the DVKT distribution of the 4 vehicles on the boundary marked in figure (a), and the dashed lines refers to typical DVKT distributions of a personal vehicle and a ridesharing vehicle.

Note that the classification cannot determine that the vehicles in group 2 are *definitely* used for ridesharing but that the travel pattern is more like a ridesharing vehicle than a personal vehicle. Average daily travel time for group 2 is 459 minutes, while it is 166 minutes for group 1. This further validates categorizing group 2 vehicles as ridesharing vehicles, since most personal vehicle drivers would not spend more than 7 hours on the road.

Besides, the travel patterns of the points on the boundary of the clusters in Figure 2 (a) (Vehicle #1 to #4) could possibly be adopted as dual-purpose vehicles (also known as part-time ridesharing vehicles) or single-purpose vehicles with possible multiple destinations of frequent visits. As the DVKT distribution of these vehicles shown in Figure 2 (c), compared to typical personal vehicles and ridesharing vehicles, the DVKT distributions of the four vehicles on the boundary have at least two peaks, and the probability density of different peaks are close, indicating the owners may operate the vehicle as part-time ridesharing vehicles or single-purpose vehicles with possible multiple destinations of frequent visits. They are classified according to the clustering results in this research, more detailed location information is necessary to identify the precise usage.

Fifty-eight (58) BEVs are estimated to be personal vehicles, and 61 are estimated to be ridesharing vehicles, aside from the 78 vehicles classified as taxis. The basic statistical parameters for the three vehicle applications are shown in Table 2. The total distances traveled for personal vehicles, taxis, and ridesharing vehicles in the sample data are 467,000 km, 2,335,000 km, and 1,599,000 km, respectively. The active days rates, defined as the number of days a vehicle is used divided by the number of days it is monitored (De Cauwer et al., 2015), are 35.36% for personal vehicles, 45.38% for ridesharing vehicles, and 66.29% for taxis.

Table 4. Statistical results classified according to vehicle usage

	Personal Vehicle	Taxi	Ridesharing Vehicle
No. of vehicles	58	78	61
Car-days*	8,553	21,563	11,544
Active days rate	35.36%	66.29%	45.38%
Total distance (km)	466,759	2,335,369	1,599,198

* Car-day refers to one car per day.

Subsequent analyses in this paper are based on this statistical classification of personal vehicles, taxis, and ridesharing vehicles.

3.4. Gamma Distribution of Daily Travel Distance

For a more convenient discussion of travel patterns, the gamma distribution is assumed for daily driving distance and fitted using the DVKT data. Lin and Greene (2011) were the first to use the gamma distribution for daily driving distance in the analysis of plug-in electric vehicle energy consumption due to its non-negativity, skewness flexibility, and specification ease. The gamma method was later validated by Lin et al. (2012) using GPS-tracked driving data, and it has been commonly adopted in plug-in electric vehicle energy studies (Lin, 2014, 2012; Lin et al., 2018).

The gamma distribution is described as follows (Lin, 2014, 2012; Lin et al., 2018):

$$y = f(x|\alpha, \beta) = \beta^{-\alpha} x^{\alpha-1} e^{-x/\beta} / \Gamma(\alpha) \tag{1}$$

The gamma distribution can be specified with two parameters: scale β and shape α. The gamma distribution expectation, which can be expressed as α·β, can be estimated by dividing the annual driving distance by 365. The mode of the gamma distribution is (α -1)β and can be approximated by the daily round-trip distance to work or the most frequent destination. As a result, the gamma distribution can be specified by knowing the annual distance and the commuting distance, as described in Lin et al. (2018).

3.5. Electricity Consumption Based on SOC and Corresponding Range

The SOC is used to estimate energy consumption. SOC indicates the remaining capacity of a battery expressed as the percentage of the battery's maximum-rated A•h capacity (SAE, 2010). According to Lu et al. (2016), during the discharge period, the electric energy changes approximately linearly with SOC, which can be expressed as follows:

$$\Delta E \approx k \Delta SOC \tag{2}$$

where k is the battery capacity, ΔE is the change in energy measured in kWh, and ΔSOC is the change in the state of charge. Since the SOC dropping from 100% to 0% means that a fully charged battery (battery nominal capacity [E_0]) is used until fully discharged, k can be estimated as $E_0/100$.

Therefore, for the 30.4-kWh and 25.6-kWh batteries equipped in the taxi and personal-use BEVs in this study (Table 3), the energy consumed can be estimated by multiplying the SOC variation by the coefficients of 0.304 and 0.256, respectively:

$$\Delta E = 0.304 \Delta SOC \quad \text{(for taxis)} \tag{3}$$

$$\Delta E = 0.256 \Delta SOC \quad \text{(for personal vehicles and ridesharing vehicles)} \tag{4}$$

Rather than focusing on electricity consumption (EC), BEV consumers are more sensitive to driving range, which is also the primary issue of concern for BEVs in the media (Gilanis, 2016; Stevenson, 2018). Based on the actual energy consumption

(EC_{actual}), the actual BEV driving range ($range_{actual}$), affected indirectly by ambient temperature, driving style, and vehicle application, can be calculated using Equation 5.

$$range_{actual} = E/EC_{actual} \tag{5}$$

E refers to the battery capacity of each BEV model (30.4 kWh and 25.6 kWh in this study), and EC_{actual} is measured in kWh/100km.

To better understand the correlations between the method and the results, the travel patterns (Section 4.1) are related to Step 8 and are illustrated in Section 3.3. The charging patterns (Section 4.2) are related to Step 6. The electricity consumption in Sections 4.3–4.5 are related to Step 9 and are illustrated in Section 3.5. The range in Section 4.6 is related to Step 9 and is illustrated in Section 3.5.

4. Results

4.1. Travel Patterns

The average DVKT of personal vehicles, taxis, and ridesharing vehicles in Beijing are 44.8 km, 110.2 km, and 113.8 km, respectively. The fitted gamma distributions of the daily travel distance of each vehicle application based on the method in Section 3.4 are shown in Table 5, and the α and β values of the gamma distributions are listed in Table 5. The correlation coefficients with the actual DVKT exceed 0.8, indicating that the gamma distribution has a high fitting accuracy.

Table 5. Median, average, and gamma distribution classified according to vehicle application

	Personal Vehicle	Taxi	Ridesharing Vehicle
Median	40.3	109	114.1
E[X]	44.8	110.2	113.8
Gamma distribution, shape α	2.7	10.8	1.9
Gamma distribution, scale β	16.6	10.2	59.9
coefficient	0.96	0.88	0.80

Electric personal vehicles typically travel shorter distances than electric taxis and ridesharing vehicles. The median DVKT of personal vehicles is 40.3 km, and the mode is 28.2 km. The expected DVKT of personal BEVs (44.8km) is 15% more than that of conventional vehicles in Beijing (39 km) (Wang et al., 2014), possibly due to different data source. This indicates that most travel demand should be met by the 160-km personal BEVs. The lower DVKT of electric vehicles is probably due to the lower proportion of long-distance trips for BEVs, but more research is needed to determine the exact cause.

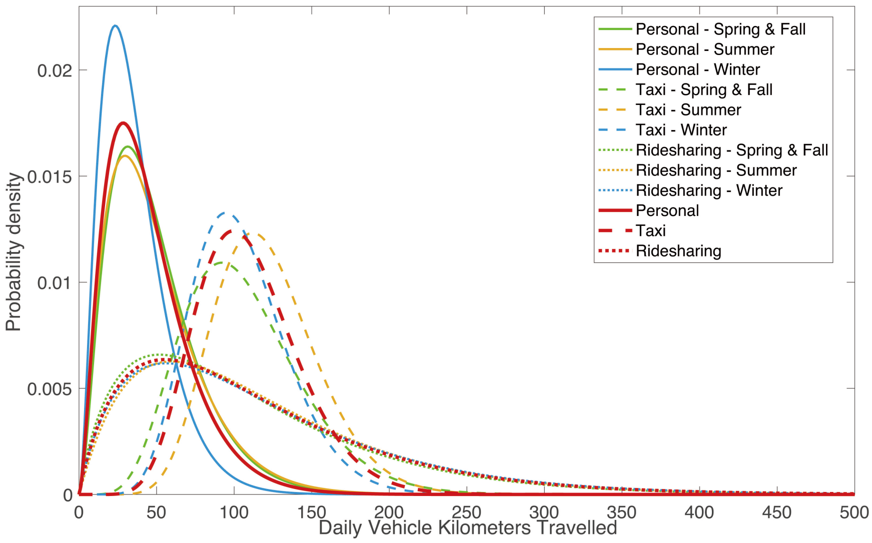


Figure 3. Fitted DVKT gamma distribution of vehicles for different uses (personal, taxi, and ridesharing) during different seasons (spring/fall, summer, winter).

The red curves represent the comprehensive curves for each vehicle application. The green curves represent DVKT in spring/autumn; the yellow curves represent DVKT in summer; and the blue curves represent DVKT in winter.

In this dataset, ridesharing vehicles have the longest DVKT, with a median of 114.1 km (Figure 3), which indicates that people are willing to charge more frequently when needed. The same 160-km BEVs, if used for ridesharing, have an average DVKT of 113.8 km, much higher than the 44.8 km DVKT of electrical personal vehicles in Beijing. As shown in Figure 4, 24% of ridesharing DVKT exceeds the range of the 160-km BEV. For personal vehicles, less than 1% of DVKT exceeds that range. This means that ridesharing drivers must charge more to meet the travel demand. This is a strong indicator that a driving range of 160 km is close to serving the range requirements of personal drivers as well as the much higher travel demand of ridesharing services—although at a higher charging frequency (Figure 5)—with the existing public charging infrastructure in Beijing.

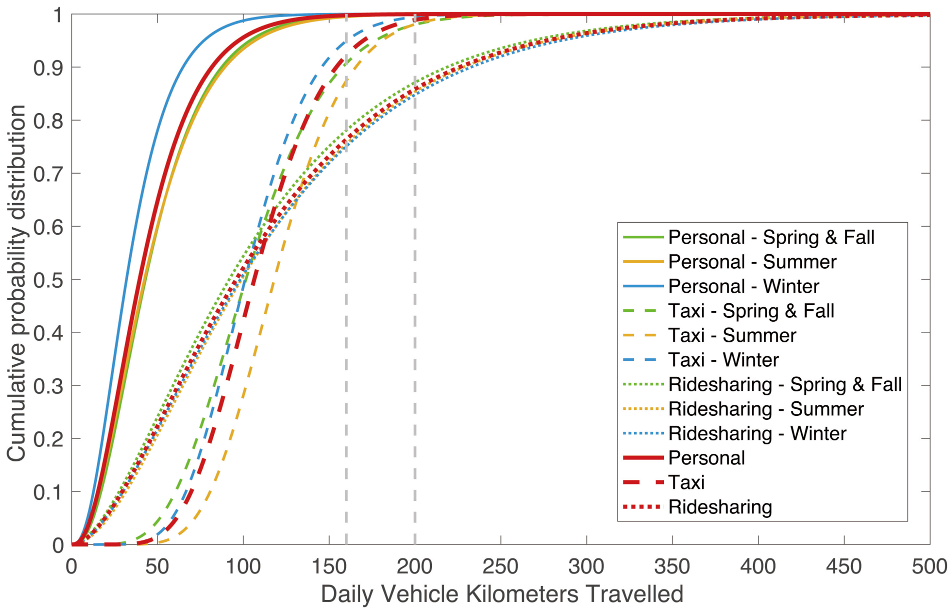


Figure 4. Accumulated DVKT gamma distribution of vehicles for different uses (personal, taxi, and ridesharing) during different seasons (spring/fall, summer, winter)

The red curves represent the comprehensive curves for each application. The green curves represent DVKT in spring/autumn; the yellow curves represent DVKT in summer; and the blue curves represent DVKT in winter.

As the dashed lines shown in Figure 3, the DVKT of taxis typically ranges from 80 to 160 km, with a median of 109.0 km. Taxis in Daxing District travel longer distances than personal-use vehicles—a median DVKT of 109 km for taxis vs. 40.3 km for personal vehicles. However, they travel a shorter distance than urban taxis, which traveled 183 km per day on average in Beijing in 2017 (Beijing Transport Institute, 2019). This is mainly because the electric taxis in our sample operate in Daxing District only. The core business for suburb taxis is to shuttle consumers from subway stations to destinations less than 5 km away.

As shown by the solid lines in Figure 3 and 4, the travel distance of personal vehicles has the greatest seasonal variation even though they are primarily used for commuting. The DVKT across different seasons are sorted according to travel dates shown in Figure 3 and 4. They are divided into three groups: (1) spring and fall, (2) summer, and (3) winter.[1] Beijing has a temperate continental climate with distinct seasons. Note that a rare heavy snow with a sudden temperature drop occurred in November 2015. Operation data for November 2015 is left out to better reflect normal

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[1] Spring is defined as March, April, and May; summer is defined as June, July, and August; fall is defined as September, October, and November; and winter is defined as December, January, and February.

circumstances. The median DVKT for personal vehicles is 31.6 km in winter and 46.0 km in summer due to summer vacation travel and fewer long trips taken in winter.

4.2. Charging Patterns

Charging frequency is the highest for ridesharing vehicles, followed by taxis and personal vehicles. Charging events are defined by Step 6 in Section 3.2. Figure 6 shows the charging interval distributions grouped by vehicle application and season. The average charging intervals are 38 h for personal vehicles, 20 h for taxis, and 16 h for ridesharing vehicles. This means that taxis and ridesharing BEVs charge at least once a day. The cumulative frequencies of charging within every 48 h (2 days) are 76% for personal vehicles, 93% for taxis, and 95% for ridesharing vehicles. A vehicle's charging pattern is the result of many factors, such as travel patterns, energy consumption, and charging infrastructure convenience. Charging frequency is significantly affected by a vehicle's use and seasonal changes.

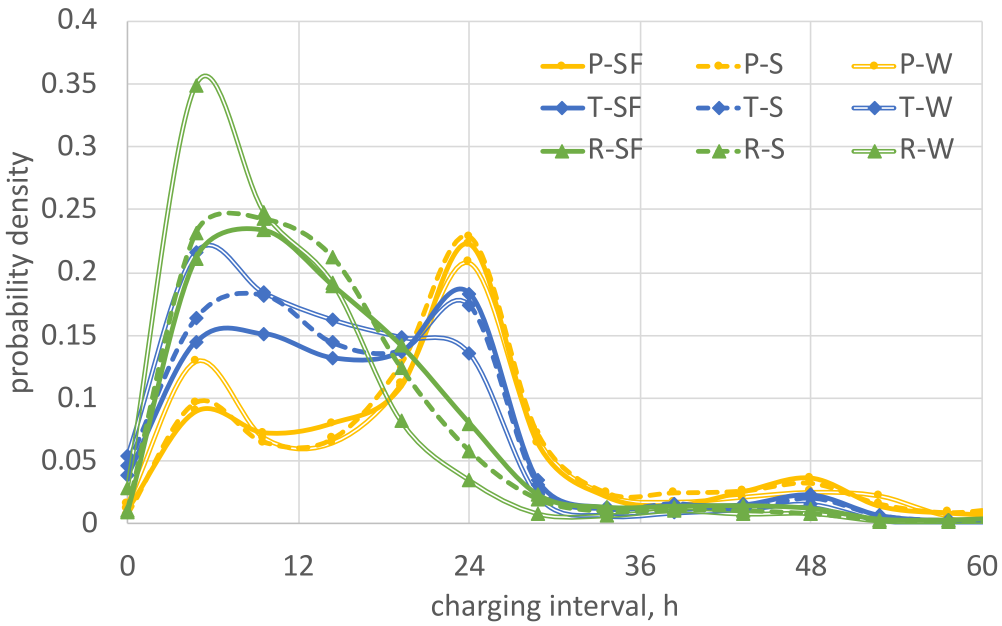

Figure 5. Charging frequency of BEVs for personal use (P), taxi operation (T), and ridesharing (R) during different seasons: spring/fall (SF), summer (S), and winter (W)

The charging frequency of personal vehicles has a "double peak," with peaks at the 8-hour and 24-hour charging intervals. As shown by the yellow lines in Figure 5, the average charging interval for personal cars is 1.6 days. Twenty-three percent (23%) of charging events appear once a day, forming the higher peak, and the lower peak (8%–13% of charging events) occurs at an interval of 8 h. The higher peak is mainly because personal BEV owners usually have a fixed home charger and charge regularly after daily commuting trips. Owners may choose to charge during the day at work, if possible, resulting in the lower peak. This is also in line with the Beijing Transport Institute estimate of 2.7 to 4.8 times per week (Hai, 2017). Also, due to the regularity of daily commuting trips, the seasonal variation of the charging frequency for these vehicles is small—workplace charging events increase by only 4% in winter.

The charging frequency of taxis is indicated by the blue lines in Figure 5. The charging frequency of taxis has a clear seasonal variation because of range limitations caused by colder weather. The average charging interval for taxis is 20 h, with a somewhat even distribution from 6 to 24 h. The average charging interval is 38% shorter in winter (16 h) than in spring/fall (26 h). More than 71% of taxis charge twice a day in winter, while the number is 63% in summer and 57% in spring/fall. Charging at the 4-h interval in winter accounts for 22% of charging events, 24% higher than in other seasons. The frequency of charging once a day in winter is only 14%, while it is 18% in spring/autumn and 17% in summer. Taxis have higher charging requirements compared to personal vehicles.

As shown by the green lines in Figure 5, ridesharing vehicles have the highest charging frequency, 16 h on average, mainly due to the long DVKT and smaller battery compared to taxis. Seasonal variation is also significant, as the average charging interval is 12 h in winter and 20 h in spring/autumn. About 35% of charging events appear within the 4-h interval in winter, while in other seasons, the charging interval is dispersed between 4 and 20 h. The high charging frequency is primarily due to the smaller battery equipped by the personal BEVs used for ridesharing although it is also due to the longer travel distances of ridesharing vehicles operating downtown. The charging frequency of ridesharing vehicles is significantly higher than that of personal BEVs due to their longer travel distances—their batteries are the same size. Thus, longer-range BEVs are needed for ridesharing vehicles. It also indicates that the charging infrastructure in Beijing is sufficient for these vehicles, with more than 40 thousand chargers available in Beijing as of the end of 2018 (EVCIPA, 2019).

4.3. Electricity Consumption by Application

The average real-world electricity consumption of BEVs in Beijing is 17.6 kWh/100 km for personal vehicles, 16.8 kWh/100 km for taxis, and 17.1 kWh/100 km for ridesharing vehicles. These consumption values exceed NEDC test results by 10%

for personal vehicles and taxis and by 7% for ridesharing vehicles. Figure 6 and Figure 7 show the distribution of actual electricity consumption values for the three vehicle applications, as derived from the SOC using the method described in Section 3.5. For most vehicles, EC is concentrated from 14.5 to 19.5 kWh/100 km. The real-world electricity consumption of personal vehicles is 3% higher than that of ridesharing vehicles. Since the same BEV model is used for both vehicle applications, this difference is due to driving behavior differences. It is possible that ridesharing drivers know more about road conditions and are more skilled at driving to maximize fuel economy (e.g., making better use of regenerative braking and avoiding aggressive acceleration or deceleration). It could also be caused by a difference in trip distance, as ridesharing is associated with greater use intensity and longer trips. However, the reason for this difference is not clear and needs more research.

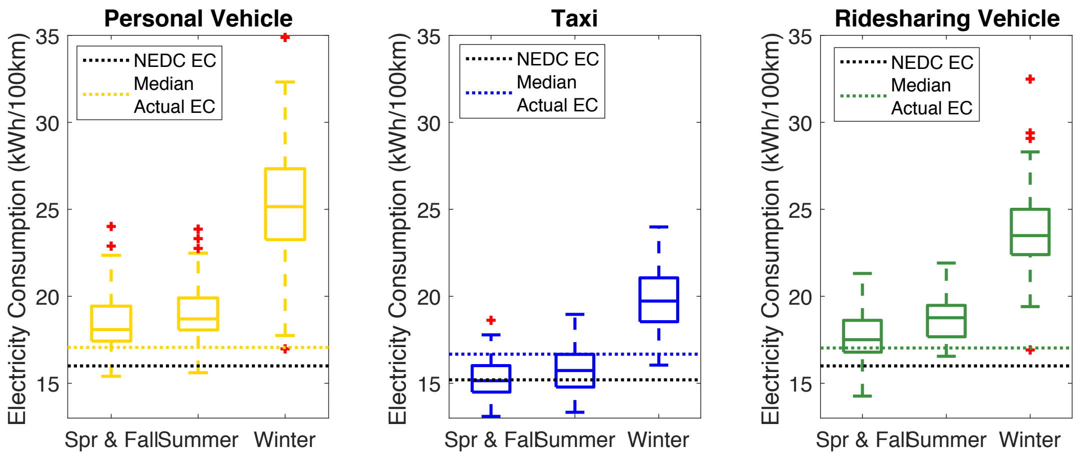

Figure 6. Electricity consumption (EC) of the three vehicle applications in different seasons in this study

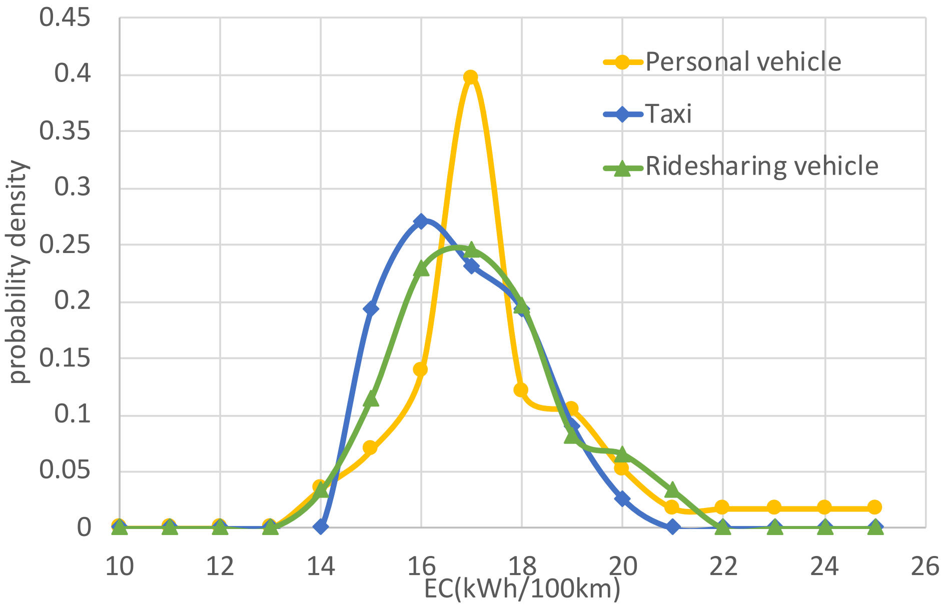

Figure 7. Electricity consumption distribution for the three vehicle applications in this study

Moment analysis is adopted to describe the differences in energy consumption of the different vehicle applications. Personal vehicles have the worst average energy economy and the most extreme values due to the volatility of driving patterns. The first four moments of EC are listed in Table 6. The first central moment, the average, is an indication of the average energy consumption level. Average electricity consumption of personal vehicles, taxis, and ridesharing vehicles are 17.6, 16.8, and 17.1 kWh/100 km, respectively, slightly higher than median electricity consumption due to some extremely high values. The second central moment, variance, is a description of the degree of dispersion. The variance in the EC of personal vehicles is significantly higher than that of taxis and ridesharing vehicles (4.45 vs. 1.67 and 2.60), indicating large variation in driver characteristics, including driving skills and driving habits. The third central moment, skewness, is a parameter that indicates the direction in which the energy distribution distance deviates from the means. Positive skewness of the three vehicle applications indicates energy consumption is usually higher than the mean. Finally, the fourth central moment, kurtosis, describes the appearance of extreme values. Personal vehicles have the most extreme high values, combined with positive skewness. This may be due to different driving preferences, for example, the personal BEV owners may drive more aggressively with extreme high energy consumption.

Table 6. The first four central moments of EC

	Energy Consumption			
Vehicle Application	Mean (kWh/100 km)	Variance $(kWh/100\ km)^2$	Skewness $(kWh/100\ km)^3$	Kurtosis $(kWh/100\ km)^4$
Personal use	17.60	4.45	12.76	101.18
Taxi	16.78	1.67	0.86	4.23
Ridesharing	17.13	2.60	2.10	16.08

4.4. Electricity Consumption by Season

Electricity consumption increases more rapidly in winter than in summer. According to Figure 8 (a), taxi data from the study dataset is taken as an example to illustrate the seasonal variation in electricity consumption and temperature influence. Electricity consumption in spring and fall is 15.2 kWh/100 km, and it is 3.3% higher in summer and 30% higher in winter because of the use of the heating, ventilation, and air conditioning (HVAC) system and poor battery performance in winter. In summer, the use of air conditioning makes energy consumption 0.5 kWh/100 km higher than in spring and fall. Cold ambient temperatures in winter lead to increased heater use and poor battery performance, making EC 30% higher than in spring and autumn. As for the distributions, 83% of electricity consumption in spring and autumn is distributed from 14.0 to 17.0 kWh/100 km, while 78% falls within this range in summer, and 1% falls within it in winter. Fifty-nine percent (59%) of winter EC falls between 18.0 and 21.0 kWh/100 km. Therefore, for the integrated power consumption distribution, two peaks are formed, one at 15.0 kWh/100 km and another at 18.0 kWh/100 km. Besides, Figure 8 (b) and (c) illustrates the seasonal variation in electricity consumption of BEVs for personal use and ridesharing.

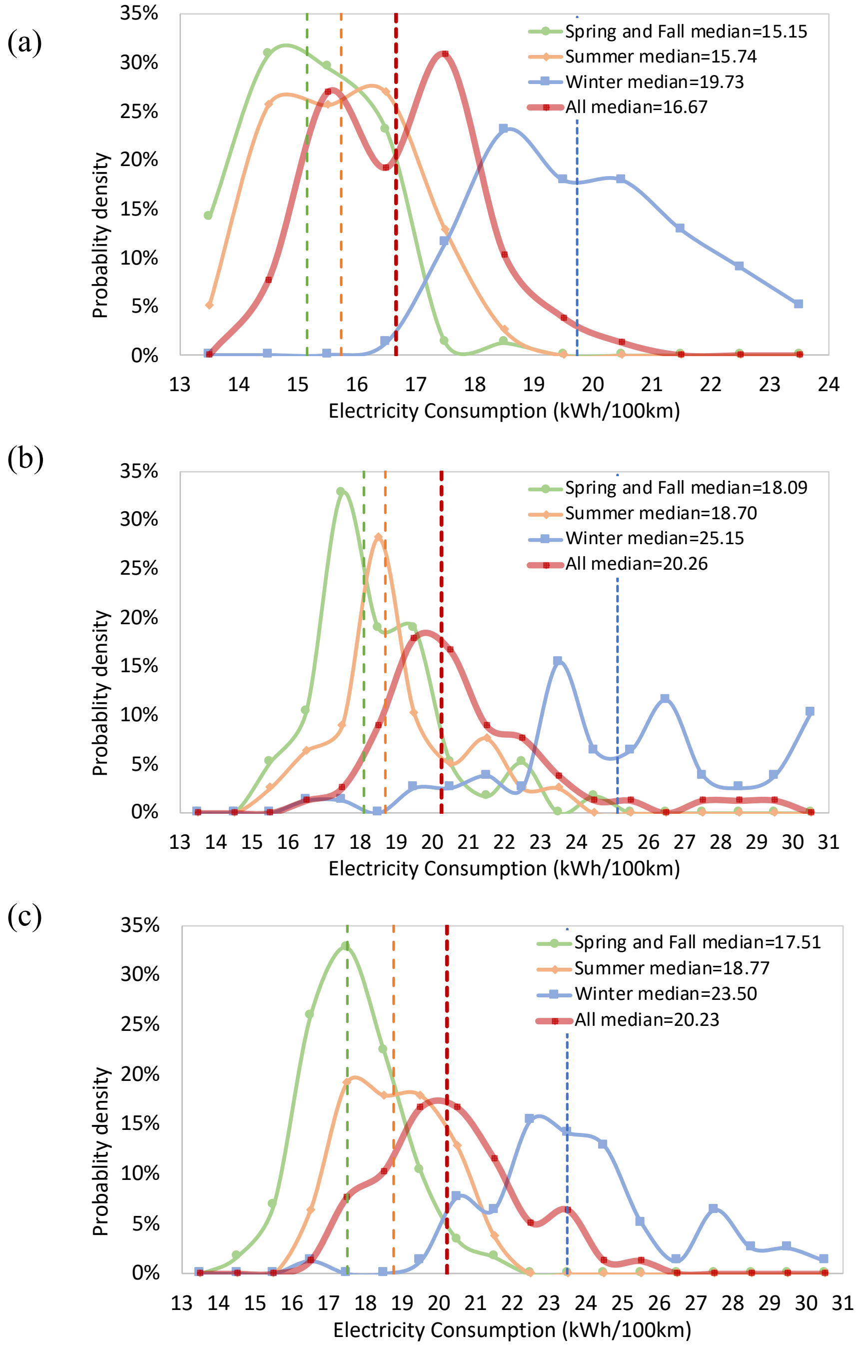

Figure 8. Electricity consumption per 100 km during different seasons of: (a) taxi, (b) personal vehicle, and (3) ridesharing.

The green curves represent spring/autumn; the yellow curves represent summer; and the blue curves represent winter. The comprehensive distribution is indicated by the red curves.

Ambient temperature is the main factor influencing electricity consumption (Figure 9). It has a clear three-stage feature, with a basin and two linear stages. The ambient temperature here refers to the average of the highest and lowest temperatures gathered from Beijing's weather report ("Historical weather requiry," 2009). EC has a low basin—a statistical average of 14.9 kWh/100 km (2% lower than the NEDC test result)—at an ambient temperature of 12°C to 28°C. EC drops from 25.9 to 14.4 kWh/100 km at 19°C and then goes up again. When the average temperature is lower than 10°C, EC increases 2.4 kWh/100 km for every 5°C decrease in temperature. When it is cold, the internal resistance of the battery increases, and the useful energy discharged by the battery decreases. That is, the energy consumption of a BEV increases in cold weather. Furthermore, a BEV doesn't have an engine and thus cannot make use of the waste heat of the engine to heat the cabin. Therefore, the HVAC system must consume electricity for heating. Since the data adopted in this research doesn't indicate when the air conditioning is in use, the main cause of high energy consumption cannot be determined. Besides, as shown in Figure 10, for taxis, the average trip distance in winter is 4.3% shorter and the number of trips in winter is 10.5% higher than that in spring and autumn. Electricity consumption is higher during start-up, especially in winter, which also possibly contributes to higher energy consumption in winter. However this pattern doesn't apply to personal vehicles and ridesharing vehicles as the number of trips are decided by the travel demands. The number of trips for personal vehicles in winter decreases due to decreased travel demands in winter shown in Figures 3 and 4. When the temperature is higher than 28°C, EC increases 2.3 kWh/100 km for every 5°C increase due to HVAC system use. Cold weather results in high electricity consumption; EC at -10°C is 73.4% higher than it is in the basin temperature range.

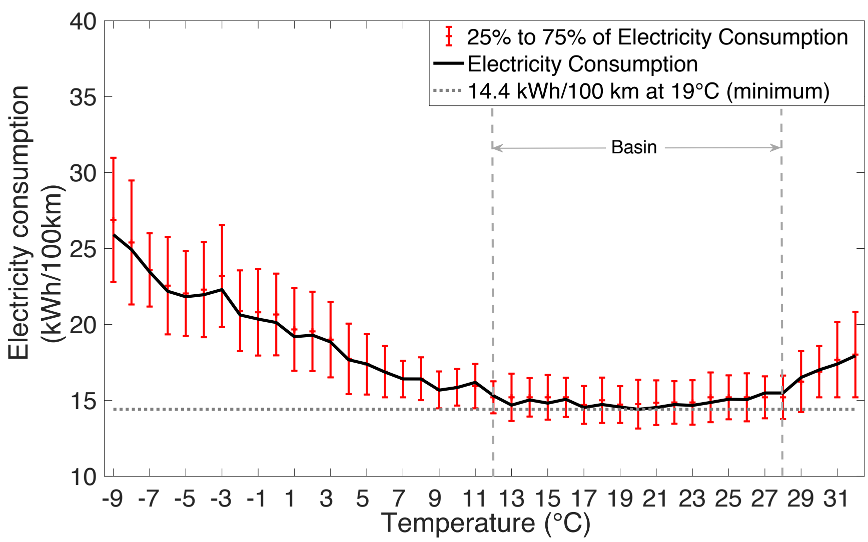

Figure 9. Electricity consumption variation with ambient temperature from -10°C to 35°C

The black solid line indicates average electricity consumption at each temperature interval. The red line indicates the 25th to 75th percentile of electricity consumption at each temperature. The grey dashed line indicates the lowest electricity consumption (14.4 kWh/100 km at 19℃) and the temperature range for the basin.

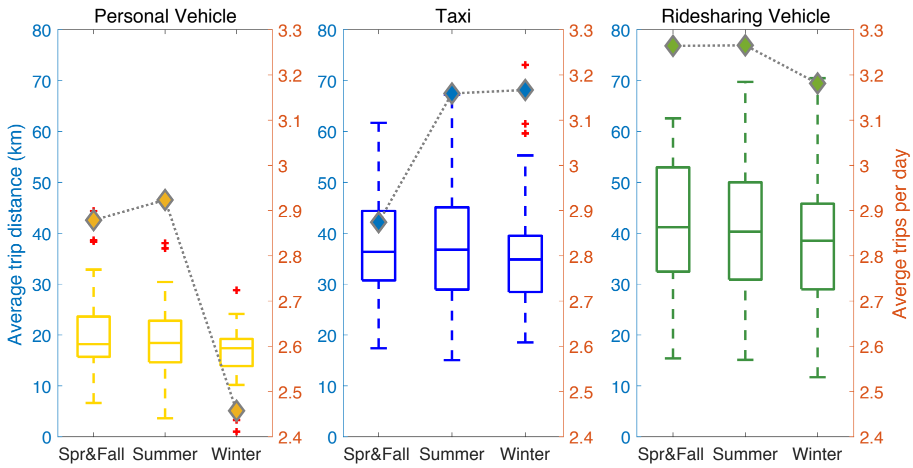

Figure 10. Average trip distance and average number of trips per day of the three vehicle applications in different seasons.

The boxplots indicate the average trip distance distribution. The diamond points indicate the average number of trips per day.

4.5. Electricity Consumption by Application and by Season

The variation in electricity consumption of different vehicle applications across the seasons is described in this section. The solid lines shown in Figure 11 indicate the median EC for vehicles of each application during each month. They share a common pattern: EC is low in spring and fall, high in the summer (especially in July), and extremely high in winter, in line with the electricity consumption variation of taxis in Figure 8.

The EC of personal vehicles is higher than that of taxis and ridesharing vehicles in summer and early winter. Taxis and ridesharing vehicles have similar energy consumption patterns over the course of a year, with a gap of less than 3% in each month. However, only in spring and late winter (February, March, April, and May) is the EC of personal vehicles close to that of taxis and ridesharing vehicles. In other seasons, the EC of personal vehicles is much higher than that of the other two. In November, December, and January, the EC of personal vehicles is 10%–15% higher than that of taxis and ridesharing vehicles. In summer and autumn, it is 5%–8% higher than that of the other vehicles. While the reason for the increased EC is unclear, personal vehicle owners may pay more attention to driving comfort and use their

HVAC systems more often or more aggressively. It is also possible that since commuter trips are shorter for personal vehicles, the HVAC may be on maximum mode to quickly get the cabin to the desired temperature for a larger percentage of each trip, which results in increased air conditioner use in summer and heater use in winter. It may also be because personal vehicle drivers are not as skilled at driving efficiently as taxi and ridesharing drivers and need more consumer education. Note that the taxis in this study are equipped with a nickel manganese cobalt (NCM) cathode battery while the other two are equipped with a lithium iron phosphate (LFP) cathode battery. The LFP battery has a poorer performance at low temperature (Jaguemont et al., 2016), which may lead to a higher gap in energy consumption between taxis and the other two vehicle applications. However, the 0.1-Hz data adopted in this research is not detailed enough to validate these explanations. Therefore, further research is warranted.

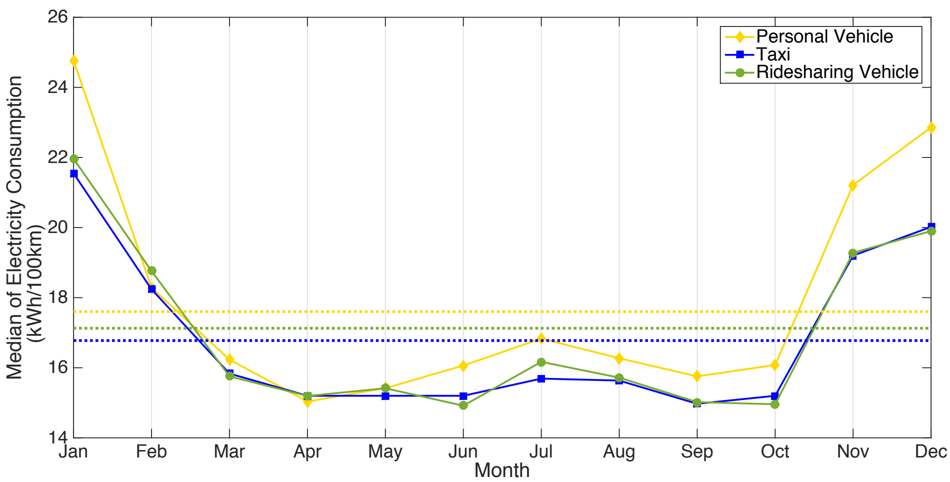

Figure 11. Electricity consumption by different vehicle applications in different months

The dashed lines indicate the average EC for the whole year for each vehicle application. Personal vehicles (17.6 kWh/100 km) consume more electricity than ridesharing vehicles (17.13 kWh/100 km), which consume more than taxis (16.78 kWh/100 km). The solid lines indicate the median EC for each month for each vehicle application.

4.6. Range

Driving range is calculated based on the method described in Section 3.5. According to Figure 12, personal BEVs experience the largest reduction in driving range compared to NEDC estimates among the three applications, especially in winter. The average BEV range for taxis is 173 km, which is 87% of the NEDC-estimated range. The average ranges for personal vehicles (126 km) and ridesharing vehicles (127 km) are 79% of the NEDC range. The actual ranges for different seasons vary significantly corresponding to the actual electricity consumption. The median of the actual driving range for taxis is 191 km in spring and fall (96% of the NEDC range), 184 km in summer (92% of the NEDC range), and 146 km in winter (73% of the NEDC range). For personal BEVs, the median range is 89% of the NEDC-estimated driving range in spring and fall, 86% in summer, and 64% in winter. For ridesharing vehicles, the median range is 91% of the NEDC estimate in spring and fall, 85% in summer, and 68% in winter. Therefore, the ratio of the actual range to the NEDC range for personal vehicles in winter is the lowest, probably because the personal BEV drivers pay more attention to driving comfort compared to taxi and ridesharing drivers and use the air conditioning and heater more often. Another possible reason is that the drivers of taxis and ridesharing vehicles are probably more sensitive to saving energy and are more skilled in doing so. The difference of equipped batteries mentioned above may also increase the range difference between taxis and the other two vehicle applications. More research is needed to quantify the actual cause of this difference.

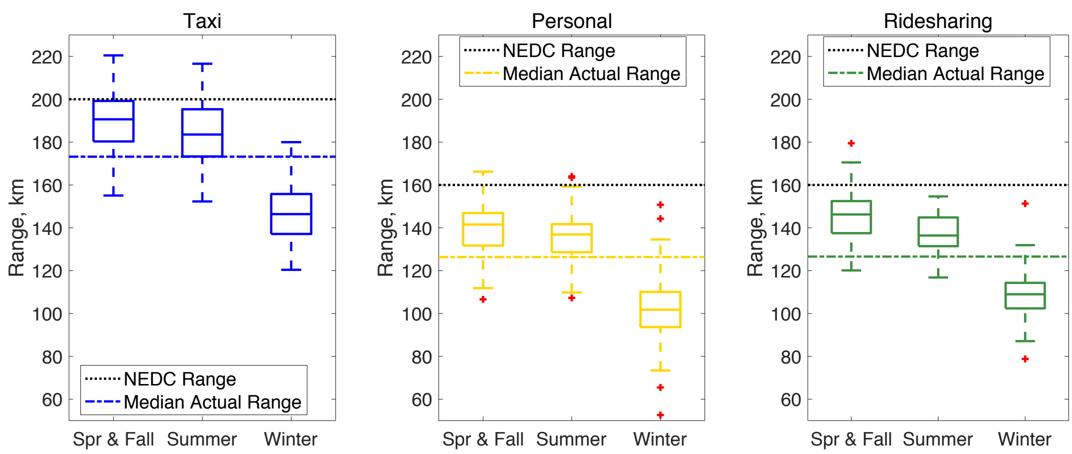

Figure 12. Actual driving range of BEVs used for different vehicle applications in different seasons

Cold weather in winter leads to high energy consumption by BEVs, resulting in lower DVKT, higher charging frequency, and range loss. This has long been an obstacle to BEV promotion, especially in the personal sector in northern China. The electricity consumption of electric vehicles needs to be optimized at low ambient temperatures. Some technologies have been adopted to mitigate range loss in winter, such as battery preheating systems by Tesla (Loveday, 2017), another diesel engine for battery heating by WM EX5 in China (WM, 2019), and liquid heating by BYD (BYD, 2019). At the same time, researchers investigate range loss at low temperatures by building up temperature-dependent models (Demircalı et al., 2018) and optimizing the thermal management of electric vehicle batteries (Demircalı et al., 2018; Rao et al., 2014; Zhang et al., 2018). Battery performance in low temperatures still needs to be addressed for technology improvement. However, due to improvements in battery energy density, many BEVs have a range of over 300 km, which is adequate for most commute distances.

5. Conclusions

Large-scale, real-world operation data from 197 vehicles of the best-selling BEV model in Beijing, China, have been analyzed to examine BEV performance characteristics across different vehicle applications during different seasons at different temperatures. Vehicles were classified by application as personal vehicles, taxis, or ridesharing vehicles using the *k*-means clustering method. Travel patterns, charging patterns, electricity consumption, and the actual range of each vehicle application in different seasons and ambient temperatures were calculated and compared.

This study is the first to use real-world BEV driving data to illustrate the operational and electricity consumption differences among personal vehicles, taxis, and ridesharing vehicles in China. The study has a few limitations.

- We do not have data on HVAC use to further explain the winter range reduction observed by the study.
- While the data is from nearly 200 vehicles, it represents only one vehicle model, and all vehicles were operating in the same city. Therefore, generalization of findings to other BEV products and regions needs further research verification.
- More detailed classification of vehicle application could be illustrated from spatial coverage of the trips with sophisticated location identification.

Still, the study contributes to a better understanding of real-world BEV efficiency, driving range, and underlying factors, with the following key findings and their implications for policy, practice, and research.

Range needs for personal travel

As our data show, a BEV with a range of 160 km can meet the range needs for most personal travel in Beijing. This is inconsistent with recent design decisions, as current BEV offerings tend to have longer driving ranges than in the past. Only 11% of the BEVs produced from 2015 to 2017 had a range of over 300 km, but this number increased to 64% in 2018 in China (Wang, 2017). Some argue that this is mainly driven by policy that favors long-range BEVs (Ou et al, 2018), while others insist that long ranges are necessary to mitigate range anxiety (EVadoption, 2018). Certainly, consumers are heterogeneous, and some will need long-range BEVs, but our findings and the findings of others clearly show that, based on actual travel patterns, the BEV range required by most consumers is much less than that indicated by policy. If so, the over-emphasis on long range may discourage the provision of more cost-effective short-range BEVs for consumers and thus inhibit market penetration of BEVs. It is possible that consumers may want more driving range than is needed, possibly due to misinformed fear or genuine willingness to pay for the low-probability inconvenience, which is a hot topic for total ownership cost research. This needs to be studied further.

Range needs for ridesharing travel

When used for ridesharing, the same BEV model was driven more and charged more frequently (up to about twice per day in the winter) to meet the longer travel demand for this application (an average DVKT of 113.8 km). This could mean that longer ranges are needed for ridesharing BEVs. It could also suggest that, with economic motivations, rideshare drivers are able to increase utilization of limited-range BEVs and are willing to make greater use of the charging infrastructure. The implication for manufacturers, governments, and researchers is the need to understand the most cost-effective improvement for rideshare BEV drivers: longer vehicle driving ranges, increased charging infrastructure, or both?

Accurate range information

The average actual electricity consumption of personal, taxi, and ridesharing BEVs exceeds NEDC test estimates by 7%–10%. This results in an overestimation of BEV ranges by 7.5%-11%. Although this is smaller than the range reduction in winter, the inconsistency is still significant and can affect consumer trust in the nominal range specification. Methods to more accurately specify BEV ranges need to be studied and implemented.

Electricity consumption differences among applications

The EC of personal vehicles is found to be significantly higher than that of taxis and ridesharing vehicles in summer and early winter. We can only speculate that taxi and ridesharing drivers have better energy-saving driving skills, but this cannot be verified by the study. Better data is needed to explain such differences.

Range as a function of ambient temperature

The lowest energy economy, near the NEDC test results, occurs at ambient temperatures of 12°C–28°C. When the ambient temperature is lower than 10°C, EC increases 2.4 kWh/100 km for every 5°C decrease in temperature. When it is higher than 28°C, EC increases 2.3 kWh/100 km for every 5°C increase in temperature. This statistical relationship is very important, but the data are limited to only one BEV model operating in one city. More data are needed to examine, confirm, or better quantify this statistical relationship. Also, more data (such as driver use of the AC system) is needed to decipher the underlying factors. A thorough understanding of BEV range in response to ambient temperature can inform technology innovation (such as developing ancillary heating devices for BEVs) and consumer operation of BEVs.

Severe range reduction in winter

Personal BEVs experience the largest reduction in real-world driving range compared to the NEDC range among the three applications, especially in winter—it is only 64% of the NEDC-estimated range. This finding confirms widely reported user complaints regarding BEV range reduction. Although we speculate that the reduction is largely due to the use of electricity for heating and poor battery performance in cold environments, this study doesn't have the data to conclude that definitively. Reyes (2016) found that operating the heater on the maximum level leads to an extra 68% to 80% reduction in range due to poor battery performance, but that study is based on a small number of vehicles. The significant range reduction observed warrants serious investigation as to possible causes and identification of mitigation technologies or strategies.

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