World Electric Vehicle Journal

Article

Actual Electricity Utility Factor of Plug-In Hybrid Electric Vehicles in Typical Chinese Cities Considering Charging Pattern Heterogeneity

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Abstract: The actual energy saving effect of plug-in hybrid vehicles (PHEVs) is usually evaluated by the electricity utility factor (UF) in a standardized charging pattern. To further evaluate the impacts of the charging pattern heterogeneity of PHEV, actual vehicle travel data are adopted to classify the charging pattern in seven typical Chinese cities and derive its impacts on actual UF. Additionally, UF curves are fitted as power exponential functions. The result shows that during daily usage, UF can reach over 0.8 for 50 km all-electric-range PHEVs for the 77% frequently charging adopters, while it is as low as 0.1 for the 3% rarely charging adopters. Comprehensive UF values at an actual charging pattern are 0.53 and 0.68 for the 50 km and 80 km all-electric-range PHEVs, and the values are 0.03 and 0.04 smaller than the standard UF, respectively.

Keywords: PHEV (plug in hybrid electric vehicle); charging pattern; utility factor; fleet

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Citation: Hao, X.; Yuan, Y.; Wang, H.; Sun, Y. Actual Electricity Utility Factor of Plug-In Hybrid Electric Vehicles in Typical Chinese Cities Considering Charging Pattern Heterogeneity. *World Electr. Veh. J.* **2021**, *12*, 169. https://doi.org/10.3390/wevj12040169

Academic Editor: Peter Van den Bossche

Received: 24 July 2021
Accepted: 26 September 2021
Published: 29 September 2021

1. Introduction

As the main segment of the global electric vehicle (EV) market, plug-in hybrid electric vehicles (PHEVs) stock was 1205, 1838 and 2377 from 2017 to 2019, and comprised of 33% to 38% of the total EV stock, according to market data statistics by the International Energy Agency (IEA). Meanwhile, the number of worldwide registered PHEVs increased by more than 500,000 per year since 2018, accounting for over 27–33% of electric vehicles [1]. For example, in Europe (Germany and United Kingdom), PHEV market share has reached over 40% of EV market. Even in China, PHEV still accounts for 21% in 2019, with well-known battery electric vehicle (BEV) friendly policies [2].

Promoting plug-in hybrid electric vehicles (PHEVs) is viewed as a promising strategy to reduce the fuel consumption and greenhouse gas (GHG) emissions to peak carbon emission in the transportation sector [3,4]. However, the complexity of the energy source makes it difficult to directly evaluate the different energy consumptions. PHEVs have two kinds of onboard energy storage, the electricity stored in the battery and the chemical energy stored in fuels (e.g., gasoline, diesel), to drive its operation alone or simultaneously [5,6]. The energy consumption in different energy modes varies dramatically with driving conditions and vehicle energy management strategies. Therefore, it is difficult to determine the actual energy consumption of PHEVs due to the combination of different energy sources, which are affected by driving conditions and driver preferences. An effective approach is needed to clarify the coupling between different energy sources while quantitatively describing their characteristics.

Electricity utility factor (UF) recommended by Society of Automotive Engineers (SAE) was widely used in research to evaluate the fuel consumption and carbon emission of

PHEVs [7–9]. Onat et al., used the travel survey results to depict the travel distance distribution of 50 states in the United States and the PHEV carbon emission reduction potential according to UF [10]. Wu et al. [11], Requia et al. [12] and Wang [3,13] take similar measures to research PHEV carbon emission in the United States, Canada and China. Currently UF has been widely adopted in the PHEV energy consumption and emission regulations in the United States [7,14], EU [15], Japan [16] and China [17]. These standards are based on different travel patterns in different countries and are effective in their own contexts.

UF was defined as the ratio of electricity-driven range (usually the charge-depleting [CD] range) to the total distance. Standard UF calculation follows the assumption that each PHEV charge once a day [7]. However, it is not always the actual situation, especially in China. Many consumers charge less than once a day due to the inconvenience to the chargers [18]. Besides, most of the research are based on the travel pattern collected from conventional vehicles instead of PHEVs. However, there are still some differences in the travel patterns of conventional vehicles and PHEVs [5]. With the commercialization of PHEVs, it is becoming possible to use PHEV travel data for a more accurate analysis of energy consumption. Smart et al., used the actual PHEV driving pattern to correct UF [19], and more actual driving and charging patterns are needed to derive actual energy saving and emission reduction analysis. Thus, actual PHEV charging behavior impacts on UF hasn't been clearly illustrated.

Actual PHEV travel data are adopted to analyze real PHEV charging patterns and evaluate its impacts on electricity UF. The ratio of actual distance between adjacent charging events to New European Driving Cycle (NEDC) tested range (A/T ratio) is defined to quantify actual charging patterns. Sales weighted actual UF and UF-fitting curves for seven typical Chinese cities with different charging patterns are derived from the data.

2. Method and Data Introduction

2.1. Data Overview

The data used in this study is obtained through the remote vehicle monitoring platform that adheres to *Technical specifications of remote service and management system for electric vehicles*, published in 2016 [20]. It is based on PHEV actual big data travel in China cities collected via National Monitoring and Management Centre for New Energy Vehicles (NMMC-NEV). NMMC-NEV is a platform collecting actual travel data from different automobile companies. Actual data includes time, speed and distance at a polling frequency of 0.1 Hz.

Travel data for seven typical Chinese cities are chosen to calculate corresponding UF curves, that is, Beijing, Shanghai, Tianjin, Xi'an Chengdu and Hangzhou, as shown in Figure 1. PHEVs are popular in the above cities with over 4000 PHEVs sold in 2018, except for Beijing (775 PHEVs sold in 2018) due to their BEV-friendly policy [21]. There are over 69,000 battery electric vehicles sold in Beijing, making it one of the biggest plug-in electric vehicle market in China [21]. Although Beijing has not yet included PHEV into plate-lottery-free new energy vehicles (NEVs), which is one of the most attractive policies for NEV consumers, PHEVs can be licensed as conventional vehicles. Here we include Beijing into our research to show more representativeness of different cities. In terms of geographical distribution, Beijing, Tianjin and Xi'an are in northern China, while Shanghai, Chengdu, Shenzhen, Hangzhou are in southern China with a higher average ambient temperature. In terms of urbanization level, Beijing, Shanghai and Shenzhen are first-tier cities, while Tianjin, Xi'an, Chengdu and Hangzhou are second-tier cities. Tiers of cities are administrative partitions by the Chinese government according to the political, economy, and city size. The first-tier areas include the urban mega areas, including Beijing, Shanghai, Guangzhou and Shenzhen. The second-tier areas refer to provincial capital cities, otherwise known as direct-controlled municipalities [22]. Plug-in electric vehicle markets develop quickly in the first-tier and second-tier cities.

Figure 1. Cities spatial distribution.

Seven PHEV models of four popular PHEV brands sold in China are selected in the above cities, including BYD Qin, BYD Tang, BYD Song, Roewe eRX5, Roewe EI6, GAC GA3S and BMW X1. These models include compact sedans, compact SUVs and medium SUVs. The vehicles share an all-electric range (AER) of 53–80 km and a NEDC-tested fuel consumption of 1.4–2.0 L/100 km. Vehicle attributes are listed in Table 1. The data comprise a total of 527 PHEVs with a coverage of seven cities, 5,830,000 km and 11,036 driving days. As the brief summary shows in Table 2, the data set includes 45–87 cars and 10,000 car-days in each city, with an average daily vehicle kilometers travelled (DVKT) of 43–55 km.

Table 1. Vehicle attributes used in this research.

Brand	Model	AER (km)	Battery Capacity (kW·h)	Motor Power (kW)	Engine Power (kW)	Fuel Consumption * (L/100 km)	Vehicle Numbers
BMW	X1 PHEV	60	14.7	70	100	1.8	97
GAC	GA3S	58	11.56	130	71	1.8	49
BYD	Qin	80	13	110	115	1.4	81
BYD	Tang (DM)	100	18.4	110	153	2	105
BYD	Song	80	16.9	120	118	1.4	15
Roewe	ei6	53	9.1	80	80	1.5	63
Roewe	eRX5	60	12	56	119	1.6	101

* NEDC comprehensive Fuel consumption.

Table 2. Data summary.

City	Beijing	Chengdu	Hangzhou	Shanghai	Shenzhen	Tianjin	Xi'an
Effective days	10,372	18,182	16,932	17,022	19,440	16,145	12,275
Total distance (km)	488,521	1,083,829	928,042	927,699	1,073,282	803,052	529,543
Number of vehicles	45	77	77	77	77	87	87
Average DVKT (km)	47.1	59.6	54.8	54.5	55.2	49.7	43.1
DVKT standard deviation (km)	56.2	64.8	64.2	58.6	62.8	54.5	55.8
Average speed (km/h)	24.8	27.6	25.8	28.3	26.8	27.8	24.2

According to the data set, the average daily vehicle kilometer travelled of each city is 52.9 km. Among the seven cities, the average daily mileage in descending order is Shenzhen (55.2 km), Hangzhou (54.8 km) and Shanghai (54.5 km), Tianjin (49.7 km), Beijing (47.1 km) and Xi'an (41.1 km) as shown in Table 2. This is mainly due to different urbanization levels and urban traffic congestion. The detailed daily mileage distribution is located in Section 3.1.

2.2. Data Processing

The data processing is carried out 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 uploading.
2. **Complete missing points.** Data overflow and data loss may lead to possible missing data. The missing points are smoothed via interpolation.
3. **Segment trips.** The data is segmented—any two adjacent data points with an interval longer than 30 min are cut into two trips. An individual standard is 30 min to keep in line with the previous research in this field [23], and can be adjusted according to research needs. The threshold of 30 min may lead to clustering of some short trips, e.g., short stops at a convenience store. However, the trip classification in this research is applied for the identification of charging events. PHEV consumers rarely charge if they stop less than 30 min. Therefore, the 30 min threshold is reasonable for this research to segment trips.
4. **Delete outlier trips.** Because the speed limit on expressways in China is 120 kph and statutory provisions limit continuous driving to 4 h [24], 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 to avoid the possible data error. At the same time, trips lasting less than 5 min 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 state of charge (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 h. The time limit aims to avoid data loss. Note 10% is also an individual threshold adopted in this research. SOC may recover a little (2–3%) after the stop according to the actual travel log data, without actual charging sessions. To avoid the miscalculation of charging, an individual threshold of 10% is adopted to exclude the stops without charging.
7. **Utility factor calculation.** Utility factor calculation is based on daily mileage distribution and the mileage distribution during two charging events. Check Section 2.3.2. for more details.

2.3. Method

2.3.1. Travel and Charging Pattern

Travel pattern includes DVKT distribution. 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 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 [25]. The gamma method was later validated by Lin et al., using GPS-tracked driving data [26], and it has been commonly adopted in plug-in electric vehicle energy studies [27–29]. The gamma distribution is described as follows [27,28]:

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

The gamma distribution can be specified with two parameters: scale β and shape α. The gamma distribution expectation, which can be expressed as $\alpha \cdot \beta$, 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. [28].

As for the charging pattern, the ratio of actual distance between adjacent charging events to NEDC tested range (A/T ratio) is defined to evaluate the actual charging pattern. Note that NEDC tested range is adopted here because it is available for all these vehicle models to make it comparable. A/T ratio is less than one if the consumers charge before the battery is exhausted, and is over one if the actual distance between adjacent charging events is longer than the NEDC tested range, which the latter is common for PHEV users due to the dual energy sources. Consumers with an A/T ratio ≤ 1.5 are defined as *frequently charging adopters*, 1.5 < A/T ratio ≤ 5 are *occasionally charging adopters*, and A/T ratio > 5 are defined as *rarely charging adopters*. Compared to commonly used charging frequency, A/T ratio removes the vehicle CD range variation effect and can clearly illustrate the consumer charging preference.

2.3.2. Utility Factor

Only the driving distance and range of PHEV (i.e., the nominal or actual range) are required for the derivation of UF. If the daily distance travelled, depicted by d_k, is less than or equal to the CD range, depicted by D, then 100% of the driving occurs in the CD mode. In turn, if d_k is higher than D, then the CD range divided by the total miles defines the driver's fraction of the CD mode traveled. Thus, UF is defined as the sum of the minimum of either D or the driving distance of d_k, divided by the sum of all distances covered. This calculation is expressed as:

$$\mathrm{UF}(D) = \frac{\sum_{d_k} \min(d_k, D)}{\sum_{d_k} d_k} \tag{2}$$

Furthermore, actual UF is defined as $\mathrm{UF_a}$ based on actual charging frequency. Considering actual charging frequency, d_i is replaced by actual distance traveled during two charging intervals (d'_k) in the calculation, and the $\mathrm{UF_a}$ can be expressed as:

$$\mathrm{UF_a}(D) = \frac{\sum_{d'_k} \min(d'_k, D)}{\sum_{d'_k} d'_k} \tag{3}$$

To easily apply the UF curve in energy saving and carbon emission analysis in the regulations, power exponential function is adopted to fit the UF curve as:

$$\mathrm{UF} = 1 - \exp\left\{-\left[C1\cdot\left(\frac{x}{norm_{dist}}\right) + C2\ + \ldots + C9\cdot\left(\frac{x}{norm_{dist}}\right)^9\right]\right. \tag{4}$$

The United States, EU and Japan offered the fitting parameters of 6-order or 9-order as needed [7,14–16].

Furthermore, sales-weighted average UF in 2018 is derived from the sales-weighted utility factor curve in different cities in China. Cities with more than 1000 PHEV sales in China accounted for 83% of PHEV sales in 2018 [21]; travel pattern in these cities were approximated by the above seven cities with existing data according to the city level and the regions. Note that sales data in 2018 is adopted as the weighted factors to illustrate the utility factor in 2018, to represent utility factor at the background of the PHEV technology and market in 2018, and the weighted factors could be different for different UF factors in different scenarios.

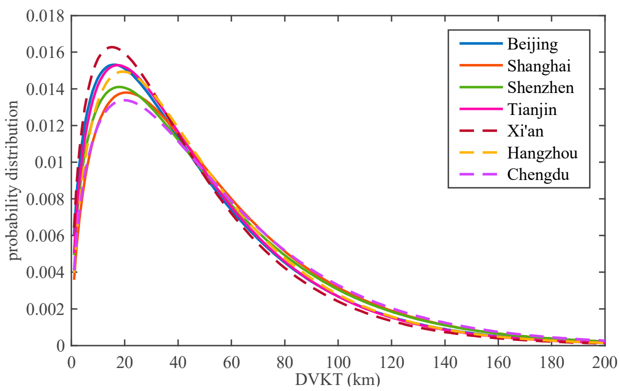
3. Results and Discussion

3.1. Travel and Charging Pattern

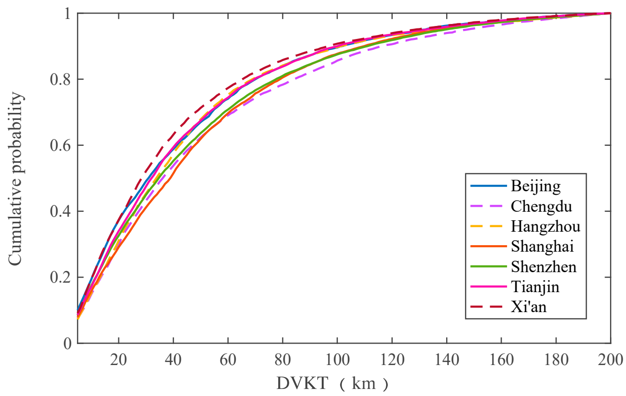
The gamma distribution fitting results of each city are shown in Table 3, and the probability distribution curve and cumulative probability distribution curve are shown in Figure 2. According to the gamma travel distribution, 59~69% of the average daily travel distance is less than 50 km, and 78~86% of the average DVKT is less than 80 km. Among them, Xi'an has the highest proportion of short DKVT (less than 50 km) days at nearly 70%; Shanghai and Shenzhen have the largest proportion of days with more than 80 km (19~20%). Furthermore, to ensure the indeed difference between different cities, ANOVA and Student's *t*-test are carried out on the daily mileages between each two cities. It turns out that the assumption of all the cities are coming from the same data source can be rejected at the significance level of 1%. As for the comparison between each two cities, it turns out that most cities can reject the same data source assumption at the significance level of 5% from the student's *t*-test, except for Beijing-Tianjin, Shanghai-Hangzhou and Shenzhen-Chengdu, indicating different travel patterns are representative among cities. Moreover, Beijing and Tianjin, Shanghai and Hangzhou are very close to each other, and it is acceptable to have similar travel patterns. It is necessary to further understand the travel heterogeneity between Shenzhen and Chengdu with more data, which is not available in this research. Check the Appendix A for the ANOVA and Student's *t*-test.

Table 3. DVKT fitted gamma distribution.

City	α	$1/\beta$	DVKT $\leq$ 50 km (%)	DVKT $\leq$ 80 km (%)
Beijing	1.51	31.37	64.0	84.0
Chengdu	1.58	34.23	59.8	78.4
Hangzhou	1.66	29.17	65.8	84.0
Shanghai	1.65	31.76	59.3	80.5
Shenzhen	1.54	33.36	60.9	81.0
Tianjin	1.58	29.95	65.1	83.8
Xi'an	1.52	29.31	69.1	86.0



(**a**)



(**b**)

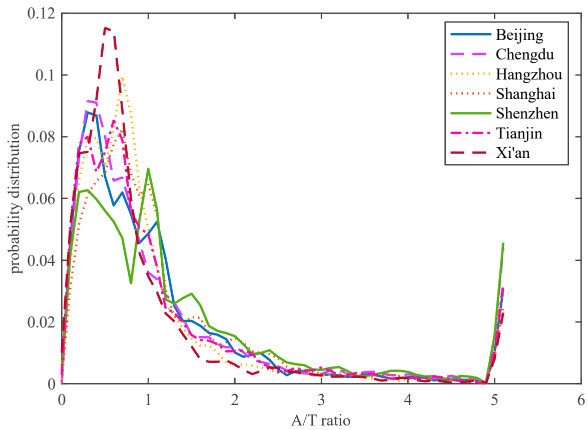
Figure 2. Fitted DVKT Gamma distribution (**a**) probability density distribution (**b**) cumulative probability density distribution.

The ambient temperature impact on DVKT is illustrated via the daily mileage variation in different seasons. As shown in Table 4, DVKT varies significantly with different seasons, especially in the cities with distinct four seasons. In Beijing, Shanghai, Tianjin, Chengdu and Hangzhou, there are fewer trips in winter due to the low temperature; therefore, the DVKT difference between winter and summer can reach up to 7–14%. However, DVKT difference between summer and winter in Shenzhen is only 4%, where the average yearly ambient temperature is 20 °C. Here spring covers March, April, May, summer covers June, July, August, autumn covers September, October, November, and winter covers December, January and February.

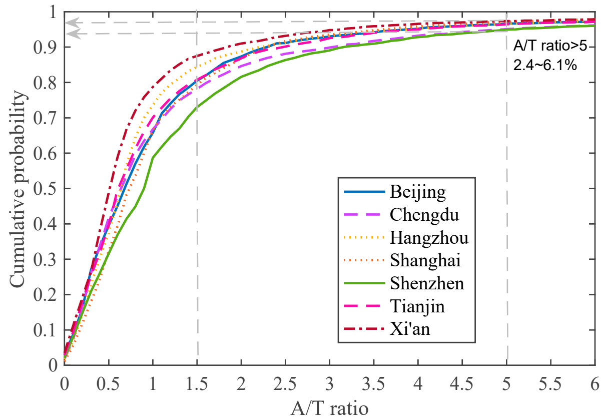
Table 4. Average daily vehicle kilometers travelled in different seasons.

City	Spring (km)	Summer (km)	Autumn (km)	Winter (km)
Beijing	44.9	55.3	50.6	49.3
Chengdu	59.7	64.1	63.1	59.7
Hangzhou	56.3	60.4	57.6	52.7
Shanghai	58.7	61.2	55.0	53.5
Shenzhen	56.8	59.0	57.6	58.5
Tianjin	50.3	51.8	52.7	45.0
Xi'an	49.9	50.3	45.9	49.6

Average distance travelled between two adjacent charging events is 67% to 138% of NEDC tested range in the seven cities, that is, A/T ratio varies from 0.67 to 1.38 in the seven cities. As shown in Figure 3b, based on actual travel characteristics and charging behaviors, 70.5~87.4% of PHEV owners in these seven cities with an average of 77.0% are frequent charging adopters, and only 2.4~6.1% of PHEV owners rarely charge (rarely charging adopters) during daily use with an average of 3.0%. Among these seven cities, there are most rarely charging adopters in Chengdu while there are least rarely charging adopters in Shanghai, however the differences among cites are limited. Specially, there is a unique double-peak phenomenon in the range of $0 < A/T$ ratio ≤ 1.5 in Shenzhen (Figure 3a), which indicates two different charging patterns in Shenzhen.



(**a**)



(**b**)

Figure 3. Actual charging pattern in different cities (**a**) probability density distribution (**b**) cumulative probability density distribution.

Standard UF of PHEV50 (50-km-all-electric range PHEV) varies from 0.55 to 0.62, and UF of PHEV80 (80-km-all-electric range PHEV) varies from 0.71 to 0.77 as the red shadow shown in Figure 4. Among the seven cities, the UF of PHEV50 was the smallest in Chengdu, while the UF of Tianjin and Xi'an were the largest. Besides, the PHEV80 has the smallest UF at Chengdu and the largest UF at Tianjin listed in Table 5.

Furthermore, sales-weighted average UF is 0.59 for PHEV50 and 0.74 for PHEV80. Cities with more than 1000 PHEV sales in China accounted for 83% of PHEV sales in 2018 [29], travel pattern in these cities were approximated by the above seven cities with existing data according to the city level and the regions. The sales-weighted average UF is the red curve shown in Figure 4.

Power exponential function fitting is carried out based on the above UF values. According to the trips in this research, the DVKT of 400 km or more only accounts for about 1%, and the omission of this part of travel has little influence on UF research. Therefore, 400 km is set as the upper limit of daily travel mileage, and 400 km is set for trips above 400 km, with the fitting parameters listed in Table 6. The fitting is carried out as nine orders to decrease the fitting error to less than 0.015 per the Beijing example shown in Figure 5. The fitting parameters are listed to simplify the calculation in actual use.

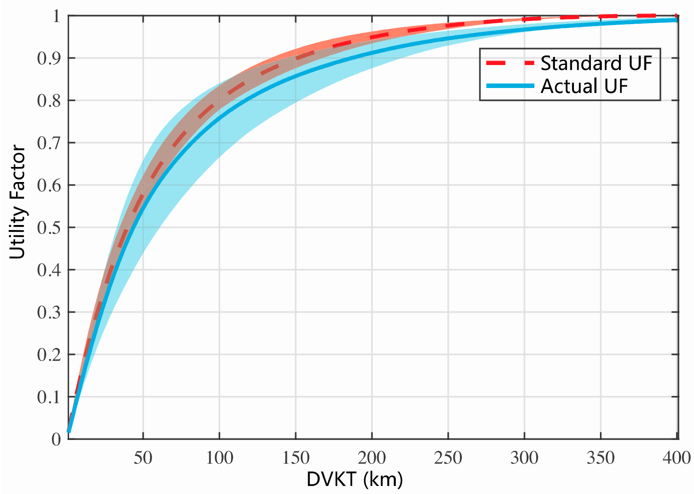


Figure 4. Standard UF and Actual UF.

Table 5. Standard UF and actual UF in the seven cities.

City	Standard UF		Actual UF	
	PHEV50	PHEV80	PHEV50	PHEV80
Beijing	0.61	0.76	0.66	0.79
Shanghai	0.59	0.75	0.52	0.76
Shenzhen	0.57	0.72	0.56	0.72
Hangzhou	0.58	0.72	0.53	0.68
Tianjin	0.62	0.77	0.51	0.66
Chengdu	0.55	0.71	0.65	0.78
Xi'an	0.62	0.76	0.44	0.59
Weighted average	0.58	0.73	0.55	0.69

Table 6. Standard UF fitting parameters.

City	$norm_{dist}$	C1	C2	C3	C4	C5	C6	C7	C8	C9
Beijing	398.00	9.46	−91.25	1366.74	−9367.48	33,665.02	−68,220.60	78,518.32	−47,888.49	12,021.37
Shanghai	397.00	8.21	−72.94	1204.37	−8548.95	31,337.30	−64,469.87	75,187.95	−46,410.66	11,777.62
Shenzhen	400.00	8.34	−82.13	1267.42	−8832.16	32,161.37	−65,899.49	76,585.96	−47,111.17	11,915.03
Hangzhou	398.00	8.41	−75.73	1199.40	−8670.57	32,304.97	−67,122.30	78,685.06	−48,667.52	12,351.97
Tianjin	398.00	9.89	−109.27	1698.94	−11,856.18	43,160.78	−88,357.88	102,543.21	−62,963.12	15,887.19
Chengdu	400.00	7.56	−45.53	708.06	−5080.46	18,969.70	−39,723.42	47,097.30	−29,529.82	7609.65
Xi'an	400.00	10.05	−95.77	1403.55	−9734.28	35,495.94	−72,870.28	84,782.31	−52,159.10	13,180.79

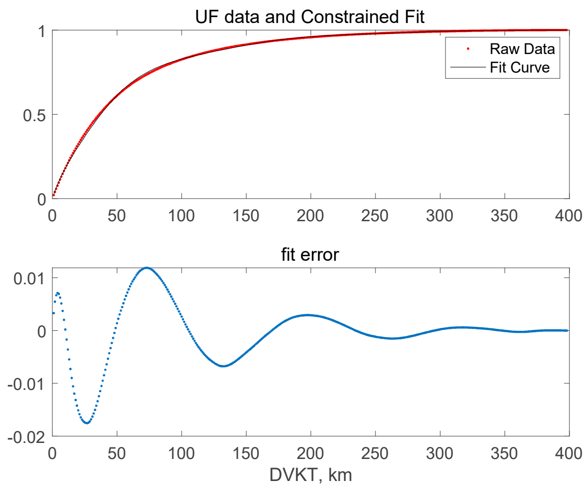


Figure 5. UF fitting error illustration (Beijing).

3.2. Actual Utility Factor and Discussion

Actual UF is derived from the Equation (3), with the sales-weighted UF at an actual charging pattern of 0.53 for the 50 km all-electric-range PHEVs and 0.68 for the 80 km all-electric-range PHEVs, which is between 23.2% to 26.2% (0.03 to 0.04) smaller than the standardized UF. In reality, this is mainly due to lower than average charging frequency. As shown in Figure 5, the dashed line shows the standard sales-weighted UF while the solid line shows the actual sales-weighted UF, and the shadows indicate the variation among different cities. The actual UF varies from 0.44 to 0.66 for the 50km all-electric-range PHEV and 0.59 to 0.79 for the 80 km-all-electric-range PHEV in different cities. Distinct inter-city UF variation indicates various charging patterns among different cities, possibly due to different charging infrastructure construction, consumer preference and charging prices. Furthermore, the power exponential function fitting of actual UF is listed in Table 7. Similar to the standard UF curves, actual UF curves are also fitted with nine order functions and the fitting errors are less than 0.015.

Table 7. Actual UF fitting parameters.

City	$norm_{dist}$	C1	C2	C3	C4	C5	C6	C7	C8	C9
Beijing	794.00	13.75	−113.92	1536.87	−10,348.24	36,662.95	−73,058.48	82,548.97	−49,385.86	12,157.30
Shanghai	794.00	14.30	−133.60	1936.53	−13,685.01	50,331.46	−103,540.98	120,320.74	−73,807.53	18,577.33
Shenzhen	792.00	11.10	−87.36	1277.10	−8988.11	32,867.44	−67,251.68	77,841.41	−47,652.14	11,994.84
Hangzhou	793.00	15.60	−116.63	1349.18	−9146.02	33,799.47	−70,566.94	83,344.16	−51,931.21	13,265.98
Tianjin	797.00	14.78	−131.13	1642.46	−11,135.11	40,621.96	−83,679.21	97,685.70	−60,284.86	15,279.12
Chengdu	797.00	14.12	−203.70	2765.22	−18,433.28	65,771.65	−133,061.46	153,048.53	−93,244.68	23,357.53
Xi'an	796.00	16.49	−106.27	958.62	−5792.00	20,157.32	−40,350.97	46,040.24	−27,843.26	6933.06

Utility factor research is the basis of energy consumption and carbon emission research. On-road carbon emission of PHEV can be simplified as the weighted average of on-road carbon emission of fuel driven distance and on-road carbon emission of electricity driven distance (zero for the on-road carbon emission) measured by utility factor. Therefore, considering the sales-weighted UF at actual charging pattern is 0.53 for the 50 km all-electric-range PHEVs, that is, over 50% distance is driven by electricity at actual charging pattern, indicating over 50% on-road carbon emission reduction potential for PHEV.

Actual UF for frequently charging adopters can reach 0.8 for the 50 km all-electric-range PHEV while it is only 0.1 for rarely charging adopters. As shown in Figure 6, bars illustrate the ratio of frequently charging adopters, occasionally charging adopters and rarely charging adopters at 77%, 18% and 3%, respectively. The UF curves in the seven cities at different charging frequencies are depicted with different colors. For frequent charging adopters, actual UF could reach over 0.8 for PHEV50 (with a range of 0.81 to 0.87) and over 0.96 for PHEV80 (with a range of 0.96 to 0.98), indicating a very significant energy saving and on-road carbon emission reduction potential of PHEV. For occasionally charging adopters, actual UF could reach a range of 0.28 to 0.33 for PHEV50 and a range of 0.45 to 0.53 for PHEV80, indicating that extending the CD range could significantly improve UF for these consumers. For rarely charging adopters, actual UF is as low as a range of 0.10 to 0.12 for PHEV50 and a range of 0.17 to 0.19 for PHEV80 and improving CD range have limited effects in such situation. Therefore, increasing CD range is effective for frequent and occasional charging adopters.

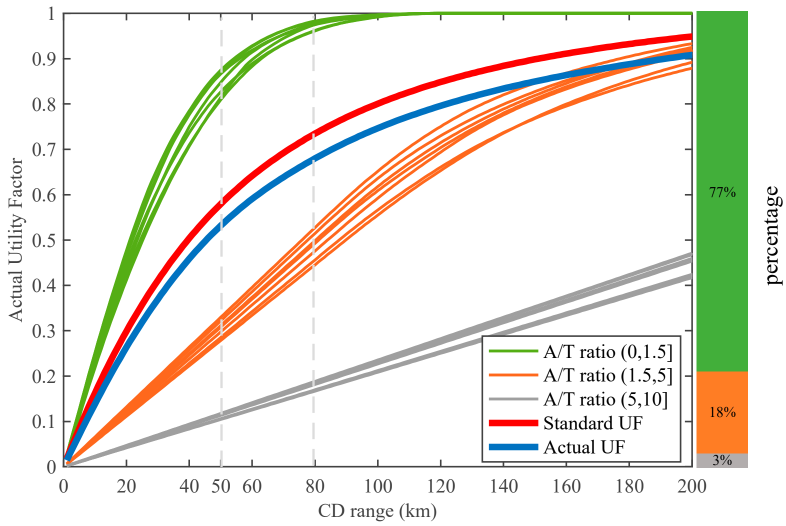


Figure 6. UF based on A/T ratio groups.

4. Conclusions

In this research, actual PHEV travel data are adopted to analyze real PHEV charging patterns and its impact on electricity UF. The ratio of actual distance between adjacent charging events to New European Driving Cycle (NEDC) tested range (A/T ratio) is defined to quantify actual charging behavior and electricity. Sales-weighted actual UF and UF at different A/T ratios are derived based on the travel pattern of seven typical cities in China. Standard and actual UF curves are fitted as power exponential functions.

The average daily vehicle kilometer traveled in each city is 52.9 km. 60−69% of the average daily travel distance is less than 50 km, and 78−86% of the average DVKT is less than 80 km. Additionally, average distance traveled between two adjacent charging events is 67% to 138% of NEDC test CD range in the seven cities, due to different charging patterns.

Sales-weighted UF at actual charging pattern is 0.53 for the 50 km all-electric- range PHEVs and 0.68 for the 80km all-electric-range PHEVs, which is 23.2% to 26.2% smaller than the standardized UF. That is, over 50% distance is driven by electricity at actual charging pattern, indicating over 50% on-road carbon emission reduction potential for PHEV.

There are 70.5% to 87.4% frequently charging adopters in typical cities in China. Only 2.4−6.1% personal PHEV adopters rarely charge during daily usage. Actual UF for frequently charging adopters is over 0.8 for the 50 km all-electric-range PHEV while it is close to 0.1 for rarely charging adopters. Therefore, increasing PHEV CD range to 80 km has a significant energy saving effect for frequent and occasional charging adopters.

Utility factor based on actual charging pattern is the basis for the analysis of energy saving and emission reduction effect of PHEV, which will largely help PHEV policy making and consumer purchasing decisions. The actual UF will help consumers accurately evaluate the suitability and cost reduction effect of PHEVs and remove purchasing concerns. Advantages for the government are shown in actual sales-weighted average UF could better estimate the energy saving and emission reduction effect owing to PHEV and help make promotion policies. Besides, it will also suggest PHEV energy saving measures and contribute directly to the carbon peaking goal through PHEV.

As for the limitation of this research, the quantitative effects of charging events and increasing CD ranges are still not clear yet. A clear mathematical expression of the quantitative effects is needed for a further research. Besides, all electric ranges and energy consumption tested under NEDC driving cycle in this research is not a good estimation due to the limitation of the driving cycle itself, and it may overestimate the energy efficiency compared to the actual situation. However, the NEDC tested range is adopted here because it is available for all these vehicle models to make it comparable. More accurate all electric range and energy consumption would be applied in this research in the future.

Author Contributions: Conceptualization, X.H. and H.W.; Data curation, Y.S.; Formal analysis, X.H. and H.W.; Investigation, X.H. and Y.S.; Methodology, X.H.; Project administration, H.W.; Resources, H.W.; Software, X.H.; Validation, Y.Y.; Visualization, X.H.; Writing—original draft, X.H.; Writing—review & editing, X.H., Y.Y. and H.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Ministry of Science and Technology of China, grant number 2019YFE0100200.

Data Availability Statement: Restrictions apply to the availability of these data. Data was obtained from National Monitoring and Management Centre for New Energy Vehicles (NMMC-NEV) and are available from the authors with the permission of NMMC-NEV.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Appendix A

Table A1. ANOVA test results for the seven cities.

	Sum of Squares	df	Mean Square	F	p-Value
Between Groups	1,443,594.9200	6	240,599.1530	66.5480	0
Error	390,480,272	108,004	3615.4242		
Total	391,923,866	108,010			

Table A2. Student's t-test results for the seven cities.

City	Beijing	Shanghai	Shenzhen	Hangzhou	Tianjin	Chengdu	Xi'an
Beijing	-	t(27296) = −8.1382, $p < 0.001$	t(29665) = −9.9723, $p < 0.001$	t(27043) = −7.4099, $p < 0.001$	t(26404) = −0.9236, $p = 0.3557$	t(26661) = −10.0174, $p < 0.001$	t(22550) = 3.5528, $p < 0.001$
Shanghai	-	-	t(36315) = −2.3418, $p = 0.0192$	t(33693) = 0.2668, $p = 0.7896$	t(33054) = 8.3748, $p < 0.001$	t(33311) = −2.8000, $p = 0.0051$	t(29200) = 12.5029, $p < 0.001$
Shenzhen	-	-	-	t(36062) = 2.5043, $p = 0.0123$	t(35423) = 10.6448, $p < 0.001$	t(35680) = −0.5829, $p = 0.5600$	t(31569) = 14.4146, $p < 0.001$
Hangzhou	-	-	-	-	t(32801) = 7.6530, $p < 0.001$	t(33058) = −2.9213, $p = 0.0035$	t(28947) = 11.5300, $p < 0.001$
Tianjin	-	-	-	-	-	t(32419) = −10.6954, $p < 0.001$	t(28308) = 4.9977, $p < 0.001$
Chengdu	-	-	-	-	-	-	t(28565) = 14.2584 $p < 0.001$
Xi'an	-	-	-	-	-	-	-

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