CARBON EMISSION VARIATIONS FOR PLUG-IN HYBRID ELECTRIC VEHICLES AFTER CORONAVIRUS DISEASE 19: AN EMPIRICAL CASE IN CHONGQING, CHINA

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ABSTRACT–Owing to the lockdowns associated with the Coronavirus Disease 2019 (COVID-19) pandemic, carbon emissions were significantly reduced. However, the accurate impacts on the personal transport sector since then remain unclear. To further investigate the influence of sudden public health emergencies on actual carbon emissions from personal electric vehicles, this paper examined the travel patterns and corresponding carbon emissions of plug-in hybrid electric vehicles (PHEVs) operating in Chongqing, China, before and after COVID-19. The results revealed that the pandemic has reshaped the travel patterns of vehicle drivers, with a 9% reduction in the post-pandemic fleet average daily travel mileage. Currently, the total daily carbon emissions of a PHEV with a range of 80 km (PHEV80) are 6.24 kg, which is 13% lower than emissions from conventional vehicles and 32% higher than those from electric battery-powered vehicles before the pandemic. Since COVID-19, there has been a 24% decrease in carbon emissions from PHEV80 vehicles for the fleet and a 30% maximum increase for individuals. Furthermore, considering the integration of 50% renewable energy into China’s power grid by 2025, PHEVs can better mitigate the fluctuations in carbon emissions associated with sudden public health emergencies compared with conventional vehicles.

KEY WORDS : Plug-in hybrid electric vehicles, Carbon emission, COVID-19, Travel pattern

NOMENCLATURE

AER : all electric range
BEV : battery electric vehicle
CD : charging depleting
COVID-19 : coronavirus disease 2019
CS : charging sustaining
DVKT : daily vehicle kilometers traveled
EC : electricity consumption
FC : fuel consumption
FUF : fleet utility factor
GPS : global positioning system
ICEV : internal combustion engine vehicle
IUF : individual utility factor
NEDC : new european driving cycle
PHEV : plug-in hybrid electric vehicle
SAE : society of automotive engineers
UF : utility factor

1. INTRODUCTION

The 2019 coronavirus pandemic (COVID-19) resulted in stringent global lockdowns to curb infection rates, leading to a worldwide decrease in carbon emissions. Consequently, daily global carbon emissions were reduced by 17% in April 2020 compared with 2019 (Le Quéré et al., 2020), eventually leading to a 6.4% reduction from the previous year (Tollefson, 2021). In China, the outbreak prompted a significant reduction in national CO2 emissions of approximately 20% in the first quarter compared with the same period in 2019 (Wang et al., 2020). However, by July 1st, 2020, the pandemic’s effects on global emissions diminished as lockdown restrictions were relaxed and some economic activities restarted, particularly in China and several European countries. Nonetheless, significant differences persisted between countries, and emissions continued to decline in the U.S., where coronavirus cases were still rising considerably (Liu et al., 2020). The Chinese economy recovered after the outbreaks of early 2020, and carbon emissions recovered quickly. Consequently, a postpandemic surge meant that China’s emissions reached a new record high of nearly 12 billion tons (Gt CO2) in the year ending March 2021, which was approximately 600 million tons (5%) above the 2019 total (Myllyvirta, 2021).

The impact of lockdowns during the epidemic and the associated reduction in transportation affected the urban
environment in terms of pollutants (Duc et al., 2021) and carbon emissions. For example, according to gross domestic product data, the freight sector contributed significantly by 32.7% reduction compared to the carbon emissions in 2019 (Han et al., 2021). According to Ou et al. (2020) although a continual lockdown (no reopening) temporarily exacerbated the demand for motor gasoline, it also helped it recover quickly to a normal level. Additionally, under an optimistic infection scenario, the gasoline demand recovered close to nonpandemic levels by October 2020. Shan et al. (2021) found that supply-chain effects contributed to a 90.1% reduction in emissions from power production in 2020, although they accounted for only 13.6% of transport sector reductions. Wang et al. (2020) tracked four-month changes in air quality during and after the COVID-19 lockdown in six Chinese megacities and compared the data with a nonlockdown scenario, and they estimated that the lockdown reduced ambient nitrogen dioxide concentrations by between 36% and 53% during the most restrictive periods, which involved level-1 public health emergency response control actions.

From the perspective of vehicle travel patterns, Zhang et al. (2021) reported that energy consumption and CO2 emissions from fuel-powered vehicles and battery electric vehicles (BEVs) were lowest during the most serious phase of the COVID-19 pandemic (February 2020). Subsequently, the pandemic was effectively controlled in China, and the energy consumption and CO2 emissions of fuel vehicles have rebounded. Therefore, it is vital to understand the impact of this sudden public health emergency on the personal transportation sector and the carbon emissions of vehicles, particularly new-energy vehicles (e.g., electric vehicles) during the COVID-19 and post-COVID phases. Furthermore, with the ongoing integration of renewable energy into the grid, the fluctuations in carbon emissions after this sudden public health emergency could motivate the government to adjust its predictions of carbon emission reductions and to establish related policies.

Reducing the carbon emissions of energy-saving vehicles (Tu et al., 2022) and electric vehicles [including BEVs and plug-in hybrid electric vehicles (PHEVs)] has been discussed extensively in a series of literature (Hao et al., 2019). One promising strategy for reducing energy consumption is the promotion of PHEVs (Wan et al., 2015) and the reduction of greenhouse gas emissions in the transportation sector (Ryu et al., 2020). In terms of types of vehicular powertrains, PHEVs can reflect actual travel needs without range anxiety (as with conventional vehicles) and can present the charging patterns (as with BEVs), which makes them an appropriate powertrain in this research. However, evaluating the carbon emissions from PHEVs is difficult because of the complexity of the energy sources involved. Simulations have confirmed that PHEVs charged by renewable electricity can reduce well-to-wheel CO2 emissions from passenger cars, but electric ranges should not exceed 200 to 300 km since battery production is CO2-intensive (Plötz et al., 2018). In charging depleting (CD) and charging sustaining (CS) modes, carbon emissions vary dramatically (SAE, 2010). Accordingly, the ratio of different modes makes determining the actual energy consumption of PHEVs difficult. The electricity utility factor (UF) recommended by the Society of Automotive Engineers (SAE) is one of the most-used parameters for measuring the ratio of electricity-driven range to the total distance. Currently, it is widely used for calculating fuel consumption (FC) and carbon emissions in the U.S., the E.U., Japan (United Nations, 2018) and China (MEE, 2016; Hao et al., 2019). For example, under the Chinese 2010 grid structure, the CO2 emission level of a PHEV with a driving range of 64 km is approximately 200 g/km (Wang et al., 2015), and the sales-weighted actual UF is 0.49 – 0.64 for PHEVs with electric ranges of 50 km and 80 km (Hao et al., 2021).

However, the abovementioned research on UF is based on fixed travel patterns in specific areas, and few studies have explored the variations in carbon emissions based on the current transformation of specific travel patterns. The COVID-19 pandemic has reshaped travel patterns with a lasting impact, and research into them will help in determining the effects of the pandemic on energy and the environment. Furthermore, with the integration of renewable energy into the grid, the fluctuations in carbon emissions due to these sudden events remain unclear to both the industry and the public.

To further investigate the influence of sudden public health emergencies (like COVID-19) on the actual carbon emissions of personal electric vehicles, especially in terms of the integration of renewable energy into the grid, this study investigated the travel patterns and corresponding carbon emissions of 25 PHEVs that operated in Chongqing, China, for an 18-month period before and after COVID-19. This constitutes useful empirical research for the postpandemic era. Fleet and individual travel patterns and UF curves were derived separately based on actual operation data, and the carbon emission factor and carbon emission per day values of the PHEVs were calculated for different percentages of renewable energy integrated into the grid. The main contribution of this research is the calculation of the carbon emission factor patterns before and after COVID-19.

This paper is organized as follows. Section 2 introduces the method and data used in this study. Section 3 derives the travel patterns and UF curves and discusses carbon emissions before and after the pandemic. Finally, Section 4 presents the conclusions and summarizes the study’s limitations.

2. DATA INTRODUCTION AND CARBON EMISSION CALCULATION METHOD

2.1. Data Overview

The PHEV travel data used in this research were derived
from the actual onboard operation data from the cooperation data platform. The dataset collected time, speed, and distance at a polling frequency of 0.1 Hz. This research used 25 personal PHEVs that were distributed across Chongqing, China. All vehicles were Chang’an CS75 PHEVs (Figure 1), which are compact sport utility vehicles with an all-electric range (AER) of 60 km and an engine displacement of 1.5 L. Table 1 presents the vehicles’ attributes. The 25 vehicles are randomly chosen in the dataset to be representative by the criteria that only one driver within this period. This period (from August 2019 to December 2021) covered 6 months before the pandemic, 2 months during it, and 10 months after. The COVID-19 timescale was from January 24, 2020, to March 9, 2020, and corresponded with the lockdown policies in Chinese cities (China.huanqiu.com, 2021; Chongqing Municipal People’s Government Network, 2021), specifically in Chongqing. The period included the implementation and removal of control measures required under the level-1 public health emergency response. It should be noted that the post-COVID effect analyzed in this research was due in December 2021, although it is limited by the availability of data. The long-term effects of the postepidemic era are unknown and are worthy of investigation.

The data exported from the monitoring platform were processed and segmented into the daily vehicle-kilometers-traveled (DVKT) distribution for each car. Data processing was completed in a Python 3 environment using open source pandas and NumPy packages. Data processing mainly included data format normalization, data cleaning, trip segmentation, and outlier deletion (Hao et al., 2021). (The supplementary attachment contains the detailed data processing steps). Trips with the same departure date were defined as trips on the same day, and distances driven by the same vehicle on the same day were accumulated as DVKT.

2.2. Travel Pattern and Utility Factor
During the pandemic, the dual impacts of COVID-19 and the Spring Festival holiday in China caused a significant decrease in both the number of trips and DVKT. From the dataset, a total of 440,793 km and 7,012 travel days were included in this research (see Table 2). As shown in the boxplots in Figure 2, the dataset was divided into the different phases of the pandemic. The ratio of travel days to total days during the pandemic was only 31 %, which is much lower than the pre- and postpandemic levels of 71 % and 49 %, respectively. Furthermore, the average daily mileage was less: the DVKT medians during the pandemic (36 km) were lower than those before and after the epidemic (44 km and 38 km, respectively).

Similar travel patterns were also validated from other research using a point-of-interest dataset in map applications and a questionnaire survey. Derived from 238,090 taxi points in 17 categories obtained from Amap in Chongqing (Nian et al., 2020), the number of taxi trips

Table 1. Vehicle attributes of CS75 plug-in hybrid electric vehicles (PHEV).

| Brand       | Chang’an       |
|-------------|----------------|
| Model       | CS75 PHEV      |
| AER (km)    | 60             |
| Battery capacity (kW·h) | 12.96          |
| Motor power (kW) | 220 (two motors) |
| Engine power (kW) | 116            |
| Fuel consumption* (L/100 km) | 1.6            |

* NEDC comprehensive fuel consumption.

Figure 1. Chang’an CS75 plug-in hybrid electric vehicle.  

Figure 2. Daily vehicle-kilometers-traveled (DVKT) distribution comparison before, during, and after COVID-19.

Table 2. Data summary.

|                   | Before COVID-19 | During COVID-19 | After COVID-19 |
|-------------------|-----------------|-----------------|----------------|
| Travel days       | 3293            | 211             | 3512           |
| All days          | 4625            | 672             | 7159           |
| Ratio (Travel days/all days) | 71 %            | 31 %            | 49 %           |
| Total distances (km) | 188,375         | 23,474          | 228,944        |
declined sharply, and the travel speed, travel time, and spatial distribution of taxi trips were significantly influenced during the pandemic (Nian et al., 2020). Moreover, in an online survey of the pandemic travel patterns of 8,330 residents in 31 provinces (including Chongqing), the proportion of Chinese residents who chose to travel by car (taxi and private car) was much higher because of COVID-19 (Jiang et al., 2020). Furthermore, some long trips were made during the level-1 public health emergency response, which may have been due to hospital commutes and possible medical usages as ridesharing vehicles. However, the validation of such assumptions requires more detailed data, e.g., from Global Positioning System (GPS) information, to determine the origin-destination data, which are not available in this research.

For a more convenient discussion, gamma distribution was assumed for the daily driving distance and was fitted using the DVKT data. The use of gamma distribution to represent DVKT distribution has been validated using real-world GPS travel data (Lin et al., 2018; Hao et al., 2021; Lin et al., 2012). The gamma distribution is described in Equation (1). The term \( \Gamma(\alpha) \) refers to the gamma function, which has the expression \( \int_0^{+\infty} t^{\alpha-1}e^{-\beta t}dt \).

\[
y = f(x|\alpha, \beta) = \beta^{-\alpha}x^{\alpha-1}e^{-x/\beta}/\Gamma(\alpha).
\] (1)

According to the definition of the gamma function and previous research, the mean (\( \bar{z} \)) of the gamma distribution is \( \alpha \beta \), which can be approximated with the average of the DVKT, and the mode (\( \bar{g} \)) is \( \left(\frac{\alpha-1}{\beta}\right) \), which can be approximated with the round-trip commuting distance for the usual commuting vehicles. Therefore, the gamma distribution parameters \( \alpha \) and \( \beta \) can be defined using the mean and mode.

As recommended by the SAE, the electricity UF is the ratio of the CD range to the total driving distance. Generally, in the CD range, vehicles operate mainly on electricity (i.e., battery), whereas in the CS range, they run mainly on fuel (i.e., in an internal combustion engine vehicle (ICEV)). Each vehicle has a different percentage of operation distance in the CD mode. If the daily distance traveled (\( d_k \)) is less than or equal to the CD range (\( D \)), 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 CD mode travel. Therefore, UF is defined as the sum of the minimum of either \( D \) or the driving distance of \( d_k \) data divided by the sum of all distances covered (SAE, 2010). This calculation is expressed in Equation (2):

\[
UF(D) = \frac{\sum_{d_k} \min(d_k, D)}{\sum_{d_k} d_k}.
\] (2)

According to this definition, the UF can be derived based on the DVKT distribution. If the travel pattern can be fitted as the gamma distribution in Equation (1), the UF can be submitted to Equation (3), as derived by Lin et al. (2018):

\[
UF(AER) = PF(\alpha + 1, \beta) + \frac{AER}{\text{mean(DVKT)}} (1 - PF(\alpha, \beta)),
\] (3)

where \( PF(\alpha, \beta) \) is the cumulative probability for a BEV with a given AER. Therefore, the standard UF at a specific AER can be derived from the mean and the mode of the DVKT. On the basis of the UF defined in Equations (2) and (3), different UFAs can be introduced into different scenarios, for example, the UF of a BEV (Duoba, 2013) at different charging frequencies (Hao et al., 2021).

Among the different UFAs defined for different scenarios, fleet UF (FUF) and individual UF (IUF) values are defined separately by the SAE according to different DVKT datasets. The FUF is a UF based on the total mileage traveled for a specific fleet of vehicles and is derived by dividing the depletion kilometers by the total kilometers traveled. This UF is particularly useful for calculating the expected fuel and electric energy consumption of an entire fleet of vehicles. On the contrary, an IUF considers all vehicles equally as opposed to DVKT weighting, which is highly weighted toward long-distance trips. The current research used FUF and IUF values to assess the travel patterns and corresponding carbon emissions separately.

2.3. Carbon Emission Calculation

The carbon emission calculation boundary of vehicles has been hotly debated whether the energy production process should be included, that is, the carbon emissions from the grid and fuel (Hao et al., 2019). The present research included the carbon emission of electricity generation in vehicle emissions, and the carbon emission of fuel only considers the fuel combustion period (Hao et al., 2019).

During usage, the carbon emissions of PHEVs include those for the electricity-driven distance and fuel-driven distance weighted by UF, as follows:

\[
CO_{2E} = UF \times EC \times CO_{2e},
\]

\[
CO_{2F} = (1 - UF) \times FC \times CO_{2f},
\]

where \( CO_{2E} \) represents the carbon emission per kilometer driven by electricity, \( CO_{2F} \) is the carbon emission per kilometer driven by fuel (which is gasoline for personal vehicles on most occasions), and \( CO_{2e} \) and \( CO_{2f} \) are the carbon emissions of 1 kWh of electricity and 1 L of gasoline, respectively. In this paper, the \( CO_{2e} \) values were obtained from Chongqing’s actual grid. Over 60% of China’s grid is supplied by coal-fired power, and in 2020,
the CO\textsubscript{2} emission via thermal plants was 832 g/kWh (China Electricity Council, 2021), which is approximated to the carbon emission factor of thermal-powered electricity. The ratio of renewable energy in the grid reached 29.8 % nationwide in 2020, with 40.0 % in Chongqing (Shoudian. BJX.com.cn, 2021). Hydropower is the main renewable power in Chongqing. Currently, the CO\textsubscript{2} emission of renewable energy power is viewed as zero. Accordingly, the CO\textsubscript{2} value in Chongqing was derived through a weighted grid composition. Considering a wire loss of 6.5 %, the CO\textsubscript{2} value was as low as 532 g/kWh in Chongqing in 2020.

Because this research only considers carbon emission during usage periods, CO\textsubscript{2}\textsubscript{f} was calculated according to the carbon balance method, and the CO\textsubscript{2} emission intensity of complete combustion of 1 L of gasoline via ICEVs was 2.37 kg (MIIT, 2021). Owing to diverse and nonagreed calculation boundaries, the present study did not consider the carbon emissions of fuel production.

$EC$ and $FC$ refer to the electricity consumption during the CD and CS periods, respectively. Additionally, this study used data on the energy consumption of CS75 PHEVs tested under the new European driving cycle (NEDC) standards, as listed in Table 3. The FC of the corresponding ICEVs and BEVs analyzed in this research is also listed to enable comparisons between ICEVs and PHEVs. Note that gaps remain between the energy consumption tested under the NEDC standard and the actual energy consumption. However, only NEDC-tested energy consumption is available for the CS75 PHEV model. Consequently, this paper used this value. More accurate actual energy consumption values should be included in carbon emission analyses.

3. RESULTS AND DISCUSSION

3.1. Travel Pattern and Utility Factor

The COVID-19 pandemic has reshaped the travel patterns of the drivers of private vehicles. To confirm an actual variation in travel patterns, a Student’s t-test was applied to the 24 PHEVs (one of the vehicles was excluded because it did not possess postpandemic data). For the 24-vehicle fleet, the t-test results were $t(6,895) = 4.633$, $p \leq 0.01$. Therefore, the postpandemic travel pattern was shown to be significantly different from that before the pandemic. In terms of individuals, the Student’s $t$-tests revealed that 8 of the 24 vehicles (37.5 %) had a significance at the $p < 0.05$ level (please see the attachment for a detailed $p$-value list). (Table).

Because there has not been a full recovery in economic and social development after the epidemic, the average fleet daily travel mileage of the 24-vehicle fleet after the pandemic is 9 % lower than before. The gamma distribution fitting was not available for the trips during COVID-19 because of the lack of data. The DVKT distributions before and after COVID-19 were fitted as a gamma distribution. The fitted parameters of the gamma distribution before the pandemic are $\alpha = 1.77$ and $\beta = 31.41$, shown as follows:

$$f(x) = 31.41^{-1.77}x^{1.77-1}e^{-x/31.41} / \Gamma(1.77),$$

where the mean is $\mu = \alpha \beta = 55.6$ km and the mode is $g = (\alpha - 1)\beta = 24.2$ km, i.e., the round-trip commute distance. As shown in Figure 3, after the pandemic, the average DVKT dropped to 50 km, which is 9 % less than that before COVID-19. To intuitively demonstrate the correlation between the gamma and DVKT distributions, the boxplots are also depicted in Figure 3. Additionally, there was a decrease in the proportion of postpandemic long-distance trips. Before COVID-19, 61 % of the days were less than 50 km, and 80 % of the days were less than 80 km; while after the pandemic, 66 % of the days were less than 50 km and 84 % were less than 80 km, which are between 5 % and 8 % lower than prepandemic figures. As the mode is approximated with the round-trip commute distance and is supposed to remain unchanged to simplify the postpandemic travel pattern variations, the mode derived from the gamma distribution decreased to 21.8 km, which is close to 24.2 km. Note that we ignored the work place changes due to

![Figure 3. Gamma distribution before and after COVID-19.](image-url)
COVID-19, although it could vary after the pandemic. Therefore, the mean fleet travel pattern after COVID-19 was assumed to be 50.0 km, and the mode was 24.2 km.

In terms of individual travel patterns, this study investigated the trends of eight vehicles, with significant travel pattern differences. After the pandemic, seven of the eight vehicles have increased their travel range by between 5 km and 45 km, and only one vehicle drives 22 km less compared to itself. This situation is also reflected in other postpandemic investigations, such as consumer surveys, where people in private vehicles are making longer trips (i.e., the impact of COVID-19 on urban travel behavior). This is due mainly to increased concern over personal health after the pandemic and worries regarding disinfection and social distancing in public transportation, such as taxis, buses, and subways. Although the dataset for the individuals is not large enough to reflect an accurate travel pattern and its corresponding carbon emissions, it indicates a trend and provides a rough range for the fluctuations in travel patterns. Accordingly, it is still a valuable empirical case for the present research. It should be noted that the dataset of 24 vehicles does indicate a trend of how travel patterns react to such public emergencies. Moreover, it can frame an initial range of travel pattern variations due to COVID-19, paving the way for subsequent research into UF and carbon emissions.

In the following calculation, a series of postpandemic travel patterns were assumed to include more individual travel patterns to reflect the effects of the pandemic. Consequently, the mean DVKT increased by 5, 10, 15, and 20 km per day to 60.6, 65.6, 70.6, and 75.6 km. As few consumers drive over 80 km/day on average in most cities in China (Wang, 2017) the present study assumed the longest mean DVKT to be 75.6 km. The commute distance remained unchanged at 24.2 km to enable comparisons due to the lack of data on personal commuting distance.

The UF can be derived from the travel pattern mentioned above according to Equation (3). The solid line in Figure 4 reveals that the UF increases with the extension in AER. The FUF for a PHEV with a range of 60 km (PHEV60) is 0.744, whereas for a PHEV80, the value is 0.848. After the pandemic, when the mean DVKT decreases from 55.6 to 50 km, the FUF of a PHEV60 increases to 0.796, which is 6.5% higher compared with prepandemic UF values. For individual UFs, when the mean DVKT increases from 55.6 to a maximum postpandemic level of 75.6 km, the IUF of a PHEV60 decreases from 0.744 to 0.598 (19.6%), whereas for a PHEV80, this value decreases from 0.848 to 0.711 (16.2%).

3.2. Carbon Emissions
The carbon emission factor (CO\textsubscript{2E} and CO\textsubscript{2F}) or the carbon emissions per kilometer driven by electricity and gasoline vary because of the UF derived from different travel patterns. As the solid line in Figure 5 reveals, as the AER increases, the distance ratio driven by electricity also increases whereas the carbon emission factor decreases for a fixed travel pattern. Before the pandemic, when the AER increased from 0 to 100 km, the carbon emission factor decreased by 31% from 128 to 98 g/km. The carbon emission factor decreased from 103 g/km for the AER of a PHEV60 to 99 g/km for a PHEV80 (4%). Therefore, increasing the AER from 60 to 80 km currently has only limited effects.

The postpandemic fleet carbon emissions decreased compared with prepandemic levels. The dashed lines in Figure 5 illustrate the fluctuations in the carbon emission factor after the pandemic. The fleet carbon emission factor of a PHEV60 after the pandemic decreases from 103 to 101 g/km, and that for a PHEV80 decreases from 99 to 97 kg/km compared with the carbon emission levels before the pandemic (2%). Therefore, the reduction in the need to
travel after the pandemic slightly decreases the carbon emission factor.

In terms of individuals, the carbon emission varies from 104 to 107 g/km for PHEV60s and 100 to 103 g/km for PHEV80s after the pandemic, which are between 1 g/km and 4 g/km (1 ~ 4 %) more compared with pre-COVID-19 levels. The carbon emission factor increases as the average DVKT for a specific AER rises because of the decrease in IUF or the distance ratio driven by electricity. In summary, there are limited variations in the carbon emission factors for PHEV60s and PHEV80s for different fleet or individual travel patterns, and they will not result in sudden increases in carbon emissions to the environment.

The total carbon emissions per day are derived from the carbon emission factors and average DVKT values. As Figure 6 reveals, the daily emissions of a PHEV80 are 1.84 kg of CO₂ from gasoline and 4.40 kg from the electricity-driven distance, totaling 6.24 kg/day. The carbon emission of a PHEV80 is 13 % lower compared with that of an ICEV, and currently, it is 32 % higher than that of a BEV. After the pandemic, the carbon emission of PHEV80s decreased to 5.03 kg/day for the fleet, which is 24 % lower compared with prepandemic levels. Moreover, after the pandemic, the carbon emissions of a PHEV80 are 20 % lower compared with those of an ICEV and 18 % higher than those of a BEV, making the former more competitive in reducing fleet carbon emissions.

In terms of the individual, if the average DVKT increases by 20 km to a total of 75.6 km per day, the carbon emissions of a PHEV80 would increase to 8.13 kg/day, which is 30 % higher compared with prepandemic levels. Compared with other powertrains, the carbon emissions of PHEV80s are 14 % lower than those of ICEVs and 26 % higher than those of BEVs after the pandemic. Therefore, PHEVs demonstrate an ability to decrease the fluctuation in the volume of carbon emissions, although the range of travel remains the main influence on carbon emissions.

3.3. Renewable Energy Grid Toward 2025
The grid’s carbon emissions will largely decrease as the ratio of renewable energy increases. By the end of the 14th Five-Year Plan (2021 ~ 2025), renewable energy will account for more than 50 % of China’s total power generation capacity. Therefore, with a 50 % integration of renewable energy, the comprehensive carbon emissions of the grid would decrease to 443 g/km. Herein, we adopted this scenario to simulate the effect of a reduction in carbon emissions due to future sudden public health emergencies.

With 50 % renewable energy in the grid, the carbon emission of PHEV60s after the pandemic will decrease to 93 ~ 98 g/km for individuals and 88 g/km for fleets. As shown in Figure 7, PHEV80s will decrease to 87 ~ 93 g/km for individuals and 84 g/km for fleets. The postpandemic carbon emissions will be 8 to 3 % lower for fleets than those in the current Chongqing grid.

The renewable electricity grid would further decrease fleet carbon emissions. As Figure 8 reveals, considering a 50 % integration of renewable energy, the carbon emissions of PHEV80s before the pandemic would be 5.50 kg/day, which is 23 % lower than that of ICEVs and 40 % higher than that of BEVs. Postpandemic fleet carbon emissions

![Figure 6. Carbon emissions of plug-in hybrid electric vehicles (PHEVs) per day: (a) Fleet; (b) Individual.](image1)

![Figure 7. Carbon emission factor variation with all-electric range (50 % renewable energy).](image2)
would decrease to 4.41 kg/day, including 1.32 kg/day of gasoline-driven carbon emissions and 3.09 kg/km of electricity-driven carbon emissions. The carbon emissions of PHEVs after the pandemic will be 0.62 kg/day, 14% lower than that in the current grid.

For individuals, when the average DVKT reaches 75.6 km, the carbon emissions of a PHEV80 will increase to 7.42 kg/day, which is 0.71 kg/day less compared with that of the current grid, although it represents a 35% increase in prepandemic levels. The variation in the carbon emissions of PHEVs before and after the pandemic is 1.92 kg/day, which lies between those of ICEV (2.29 kg/day) and BEV (1.42 kg/day). Compared with ICEVs, this is beneficial for mitigating the fluctuations in carbon emissions due to sudden public health emergencies.

4. CONCLUSION

To further investigate the effects of sudden public health emergencies (e.g., COVID-19) on the actual carbon emissions of electric vehicles, especially considering the integration of renewable energy into China’s power grid, this paper investigated the travel patterns, UF curves, and corresponding carbon emissions of 25 PHEVs that operated in Chongqing for 18 months before and after COVID-19. Fleet/individual travel patterns and UF curves were derived separately based on actual operation data, and the carbon emission factors and daily carbon emissions of PHEVs were calculated for different percentages of renewable energy integration scenarios. The main contribution of this research is the calculation of the carbon emission factors based on travel patterns before and after the pandemic.

The main findings are as follows:

The pandemic has reshaped the travel patterns of private vehicle drivers. Because there is yet to be a full recovery of economic and social development, the fleet average daily travel mileage since the pandemic is 9% lower than before. However, some private vehicle owners now travel an additional 5 to 45 km more on average per day since COVID-19, indicating the increased use of personal transport after the pandemic. Derived from the travel patterns, the postpandemic UF is negatively correlated with the average DVKT. Before the pandemic, the UFs for PHEV60s and PHEV80s were 0.744 and 0.848, respectively. After the pandemic, for the PHEV60, the fleet UF increased by 6.5% and the individual UF decreased by a maximum of 19.6%, whereas for PHEV80s, the fleet UF increased by 5.0% and the individual UF decreased by a maximum of 16.2%.

Currently, the variation in travel patterns has had little effect on the carbon emission factor per kilometer for PHEVs, and carbon emissions are governed mainly by the distance traveled. The prepandemic carbon emission factors were 103 g/km for PHEV60s and 99 g/km for PHEV80s. After the pandemic, the fleet carbon emission factor increased by 2% compared with prepandemic levels; the individual carbon emission factor increased by a maximum of 4% after the pandemic. The total daily carbon emissions of PHEV80s are 6.24 kg/day, which is 13% lower than the current levels for ICEVs and 32% higher than those for BEVs. After the pandemic, the carbon emissions of PHEV80s decreased to 5.03 kg/day for fleet values and increased to a maximum of 8.13 kg/day for individuals mainly due to the influence of the travel patterns, specifically the distance traveled.

Considering the integration of 50% renewable energy into China’s grid by 2025, the carbon emission factor of PHEVs will further decrease by 8~13% compared with current levels. In 2025, the postpandemic carbon emission factor of PHEV80s will decrease to 83~89 g/km for individuals and 88 g/km for fleets. Consequently, the fleet carbon emission will be 4.41 kg/day for PHEVs, which is 14% less than that of the current grid. However, individual carbon emissions will rise to 1.92 kg/day compared with those of the current grid. Compared with ICEVs, this will be beneficial for mitigating the fluctuations in carbon emissions following the occurrence of sudden public health emergencies.
The generalizability of these results is subject to certain limitations. For instance, this current research is limited to a small dataset of 25 vehicles. Although it constitutes a valuable empirical case for quantifying pre- and postpandemic levels in Chongqing, additional research is needed to apply the method to more vehicles in other districts. Furthermore, the corresponding GPS information will help in identifying deeper variations in travel patterns following sudden public health emergencies, like COVID-19. In future research, additional data will be collected to enrich the travel pattern dataset.

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SUPPLEMENTARY

Travel data processing

(1) Format normalization. The data format was unified and adjusted according to the time sequence to reverse the order that can occur during data transmission.

(2) Data cleaning. Points may be missing because of losses during data transmission or data overflow. Urban high-rise buildings will interfere with GPS signals and will cause position drift, and blockages in mountainous areas and tunnels may lead to the loss of GPS signals. The missing points (speed, mileage, and state of charge) for data intervals of up to 1 min were smoothed (linear interpolation) according to the data before and after the loss.

(3) Trip segmentation. The data were segmented, and any two adjacent data points with a stop longer than 30 min were divided into two trips. Note that 30 min was an assumed value in this research.

(4) Delete outlier trips. Because the speed limit on expressways in China is 120 km, and statutory provisions limit continuous driving to 4 h, single trips longer than 480 km are not permitted. To include complete data as much as possible, trips longer than 960 km (double the criteria) were deleted. Additionally, trips lasting less than 5 min or 1 km were excluded to avoid data deviation. Note that the above thresholds were based on empirical values and data quality, although they were proven effective when applied in the current research.

Student t-test values list.

| Vehicle No. | t statistic | P value | df |
|-------------|-------------|---------|----|
| 1           | 1.301       | 0.194   | 340|
| 2           | 0.772       | 0.441   | 241|
| 3           | 2.188       | 0.029   | 364|
| 4           | 3.940       | <0.001  | 303|
| 5           | 3.698       | <0.001  | 212|
| 6           | 1.788       | 0.077   | 107|
| 7           | 0.734       | 0.464   | 200|
| 8           | -1.449      | 0.148   | 74 |
| 9           | 4.255       | <0.001  | 237|
| 10          | -1.449      | 0.148   | 334|
| 11          | -1.654      | 0.102   | 74 |
| 12          | -0.722      | 0.471   | 177|
| 13          | -2.512      | 0.013   | 138|
| 14          | -0.248      | 0.804   | 270|
| 15          | -1.863      | 0.065   | 104|
| 16          | -0.658      | 0.512   | 133|
| 17          | 1.184       | 0.237   | 447|
| 18          | -1.068      | 0.286   | 299|
| 19          | -1.560      | 0.120   | 352|
| 20          | 6.202       | <0.001  | 274|
| 21          | 1.189       | 0.235   | 292|
| 22          | 3.723       | <0.001  | 134|
| 23          | 3.808       | <0.001  | 288|
| 24          | -1.199      | 0.231   | 364|