*sustainability*

MDPI

*Article*

# Vehicle Environmental Efficiency Evaluation in Different Regions in China: A Combination of the Life Cycle Analysis (LCA) and Two-Stage Data Envelopment Analysis (DEA) Methods

**Guwen Tang [1], Meng Zhang [2,*] and Fei Bu [2]**

[1] School of Management, Xi'an Jiaotong University, Xi'an 710049, China; tgwgb1123@stu.xjtu.edu.cn
[2] School of Economics and Management, Xi'an Technological University, Xi'an 710021, China; fei_bu@163.com
* Correspondence: zhangmeng89@xatu.edu.cn

**Abstract:** The efficiency of the same vehicle can vary in different regions, posing unique challenges and implications for electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs) within a country. However, most studies have regarded countries as single entities, and it is difficult to assess differences in efficiency between similar entities by simply using the life cycle analysis (LCA) method. To provide the specific environmental efficiency of vehicles in each region, in this study, we used data from 100 cities in 30 provinces in China (4 provinces are not discussed due to a lack of data) and constructed a new road congestion indicator that simulated different road conditions at different times and in different regions. A more effective method, which consisted of LCA, two-stage data envelopment analysis (DEA) and a slack-based model (SBM), was integrated to reflect the phases of LCA more clearly. The results show that the well-to-wheel (WTW) emission range of internal combustion engine vehicles (ICEVs) is 288.28–217.40 $CO_2$-eq g/km, while it is 248.20–26.67 $CO_2$-eq g/km for EVs, which means the WTW carbon emissions of EVs are generally lower than those of ICEVs (except in Heilongjiang Province). Furthermore, it was concluded that provinces with a high proportion of hydropower and a high degree of power autonomy could adjust the proportion of thermal power and inter-provincial power transmission to enhance environmental sustainability, and this would not change provincial environmental efficiency. The analysis suggests that provinces should consider both environmental protection and electricity sustainability when planning their own power development, rather than only focusing on improving environmental efficiency.

**Keywords:** life cycle analysis (LCA); carbon emissions; data envelopment analysis (DEA); regional differences; electric vehicle



**Citation:** Tang, G.; Zhang, M.; Bu, F. Vehicle Environmental Efficiency Evaluation in Different Regions in China: A Combination of the Life Cycle Analysis (LCA) and Two-Stage Data Envelopment Analysis (DEA) Methods. *Sustainability* **2023**, *15*, 11984. https://doi.org/10.3390/su151511984

Academic Editor: Silvia Fiore

Received: 13 July 2023
Revised: 31 July 2023
Accepted: 2 August 2023
Published: 4 August 2023



## 1. Introduction

In order to limit carbon emissions from the global transportation system to 1.9 billion tons by 2030, the use of electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs) is gradually increasing, and they are replacing internal combustion engine vehicles (ICEVs), serving as effective alternatives. However, in reality, EVs and PHEVs are not ideally environmentally friendly vehicles, the resulting pollution can even exceed that caused by mature ICEVs in some areas. For example, in the production stage, the lithium and cobalt in lithium batteries and the rare earth permanent magnets in electric motors will result in more pollution. In the energy generation stage, the high proportion of fossil fuels used to power EVs causes them to produce more carbon emissions than ICEVs. To evaluate carbon emissions and the environmental efficiency of EVs and PHEVs, the life cycle analysis (LCA) method has been widely used by automobile manufacturers to demonstrate the environmental efficiency and potential of their vehicles, including the Chevrolet Volt (General Motors), the Audi Q5 and Q4 e-tron (Audi), and the BMW iX3(BMW) and BYD e6(BYD).

Some LCA results have shown that the environmental efficiency of EVs and PHEVs varies between countries. For example, in Europe, Denmark, Germany, Italy, Portugal and Spain demonstrate lower carbon emissions and higher environmental efficiency when EVs and PHEVs are widely used, due to their greater utilization of clean energy from wind, solar, nuclear and tidal power [1]. In Asia, it is feasible to implement EVs on a large scale in China and India; this is not feasible in Indonesia due to high carbon emissions per unit of electricity production [2].

Although previous studies have examined the environmental benefits of promoting EVs in different countries, the results of environmental efficiency at the national level are difficult to apply at the regional level because of energy exchange between regions and more complex vehicle operating environments [3–7]. For example, Beijing's local emissions of carbon dioxide ($CO_2$), nitrogen oxides (NOx) and PM2.5 can be easily reduced due to Beijing's energy dependence on Shaanxi and Neimenggu provinces [8]. In this case, energy exchange between provinces causes the environmental efficiency of EVs to be very different in each province. These differences in environment efficiency between regions may be caused by a variety of factors, including diversified energy sources [1,9], climate change [10,11], road conditions [12], charging infrastructure [13] and so on. The existing conclusions at the national level are not sufficient to reflect the data and provide theoretical support at the regional level.

However, using LCA alone to measure environmental efficiency in different regions is not an ideal method, as evaluating differences in efficiency among similar entities is not a strong point of LCA [14–16]. Combining data envelopment analysis (DEA) and LCA into a unified framework is an innovative approach in sustainability assessment that helps to overcome the limitations of the simple LCA framework and provides a consistent framework for the quantitative benchmarking of performance indicators when evaluating multiple similar entities [17,18]. DEA can be used to evaluate the environmental efficiency of similar entities using a multiple-stage, multi-dimensional index and dynamic time [19–23], and DEA can be organically combined with other evaluation methods to make the evaluation models fit the practice [17,24]. The idea of using the LCA+DEA model is to use the LCA model to collect the life cycle index of the product and evaluate the existing life cycle results of it and use the DEA model to evaluate the efficiency of the life cycle index and results. LCA provides basic data for the calculation of the DEA model [24]. Nevertheless, there are challenges in using the LCA+DEA model, including lack of identification in inefficiency factors, the necessity of updating the original DEA model [16], and the accuracy of decision-making units (DMUs) [25], making it difficult to evaluate environmental efficiency and identify problems.

In this study, we used an updated LCA+DEA model to evaluate the differences in carbon emissions and environmental efficiency across 30 different provinces in China. We also created an indicator that was able to simulate different road conditions to reflect driving behavior across a vehicle's life cycle. The main contributions of this paper are as follows: (1) The two-stage slack-based model (SBM)-DEA method is combined with the LCA model for evaluating the environmental efficiency of vehicles, which is more consistent with the phase division of well-to-tank (WTT) and tank-to-wheel (TTW), in order to cover the full range of indicators with the aim of evaluating the vehicle life cycle as far as possible and to select key indicators for efficiency evaluation. (2) In addition, a road congestion indicator is constructed to simulate different road conditions in different regions, with the aim of describing the approximate driving conditions of vehicles in different provinces throughout their life cycles. (3) An interesting conclusion is that it is more important to maintain existing environmental efficiency than to continue to improve it when environmental efficiency is already high enough.

The rest of this paper is structured as follows: Section 2 introduces the existing research situation and the research gaps filled by this paper. In Section 3, LCA+DEA is used to calculate and display the indicators and data used in the WTT and TTW stages. Section 4 analyzes the LCA data and the causes of changes under two-stage SBM-DEA model optimization. In Section 5, the policies described in our research are summarized and discussed.

## 2. Literature Review

In this study, LCA is utilized to evaluate the environmental efficiency of vehicles. Additionally, indicators are constructed to evaluate both the spatial and temporal aspects of vehicle operation. A more scientifically rigorous LCA+DEA model is then used to measure environmental efficiency. In this section, the literature is reviewed with respect to the following two aspects: (a) the research boundaries and regional and time impacts on LCA evaluation of vehicle environmental efficiency; (b) the research and application status of LCA+DEA.

### *2.1. LCA Environmental Efficiency Evaluation of Vehicles*

LCA is a mature method that can be used to evaluate the differences in economic benefits and environmental efficiency between hybrid electric vehicles (HEVs), PHEVs, range-extending vehicles (REVs), EVs and ICEVs [2,26]. LCA studies evaluating the environmental impacts of EVs typically consider the production, use and end-of-life phases [9,27]. Advances in research have led to the inclusion of material composition and system components in the environmental comparison between EVs and ICEVs. The material composition and system components consist of a battery pack [28], an automotive frame [29] and an intelligent system [30], among which the most relevant is the exploration of battery materials. Studies have also examined the impact of battery energy density [31], production process [12] and battery aging [32] on the LCA environmental evaluation of EVs, which are also discussed. After considering the recycling stage in the LCA evaluation of EVs, the research interest in LCA evaluation of environmental efficiency of EVs increased gradually [33]. However, due to the lack of data and the difficulty in determining key indicators, the construction level of EV infrastructure [13], energy and material transportation [27,34] and EV maintenance consumption [35] require further research.

With the advancement of LCA as the evaluation method for EVs, scholars have chosen to evaluate the difference between the environmental efficiency of EVs and ICEVs more scientifically in consideration of regional or time differences. The difference in regional development affects energy and material supply, leading to differences in environmental efficiency between EVs and ICEVs in different regions [1,26]. Although electricity can be transported from other regions to alleviate pollution, this would increase the amount of environmental pressure on those regions which provide electricity [8]. Time factors can affect the environmental evaluation of EVs, as well as regional factors. Similar to Denmark, Germany, Italy, Portugal, Spain and other regions with a high proportion of clean energy [1], there is a large difference in the countries' power composition between winter and summer [36], where the loss of energy needs to be compensated by thermal power plants to ensure sufficient energy and electricity for heating, as a result of the stability of thermal power generation [37]. In addition, regional temperature characteristics mean that EVs that are not able to withstand low temperatures need to consume more energy to ensure normal running [38], thus reducing the environmental efficiency of EVs. The difference between urban roads and highways is not only a key variable in LCA environmental evaluation of ICEVs, but is also gradually appearing in the LCA environmental evaluation of EVs [12,39]. This is because EVs perform differently on urban roads versus highways compared to ICEVs [40]. It is more practical to evaluate environmental efficiency by taking regional and time differences into consideration.

### *2.2. LCA+DEA, a Comprehensive Evaluation Model*

To evaluate the environmental efficiency of similar products, processes and services, DEA and LCA are used in combination, opening the DEA "black box" and filling in the gaps intrinsic to LCA evaluation. Scholars combined LCA and DEA in order to produce a comprehensive evaluation model, referred to as LCA+DEA [41–44]. The comprehensive

LCA+DEA model has been widely used in the evaluation of environmental efficiency in the planting industry [45], aquaculture industry [46] and for agricultural products [47].

Using the LCA+DEA model involves evaluating the overall environmental efficiency of a product with LCA, and then selecting an appropriate DEA model and DMUs for efficiency evaluation [24]. Currently, the DEA models selected for use in the LCA+DEA model remain the relatively basic Banker–Charnes–Cooper model (BCC) [48], Charnes–Cooper–Rhodes model (CCR) [16] and SBM [24]. Additionally, the multi-stage DEA model, which aims to reflect the multi-stage attributes of the LCA model, has not been fully developed and is not able to accurately describe the relationship between variables at each stage of LCA. The two-stage DEA model uses simple or more complex DEA models to consider the efficiency of the total system and two subsystems at the same time. This more logical model more accurately reflects the evaluation relationship and logical connection between the two processes and the whole process [49,50]. When the LCA system contains many subsystems, it is more scientific to use the multi-stage DEA model, which contains the same number of subsystem stages. Meanwhile, the research scope of the LCA+DEA model focuses on agricultural products and is rarely applied to industrial products and services [51]. The LCA+DEA model can be used to comprehensively evaluate the environmental efficiency of products or services and optimize the overall environmental efficiency in order to obtain an optimal solution; however, it also faces the problem that the DEA model is too simple.

To the best of our knowledge, this paper presents a novel application of the LCA+DEA model for evaluating the environmental efficiency of EVs and ICEVs across different regions for the first time. The first contribution is represented by the updating of the DEA+LCA model, which replaces the original DEA model with a more rigorous two-stage SBM model that reflects the multi-stage aspect of the LCA model. This update resolves the issue associated with relying on a simple DEA model in the LCA+DEA model. Another contribution is that we firstly consider and refine the influence of both regional and time differences on environmental efficiency, and we then refine these differences into a representative indicator. Table 1 summarizes the related literature and highlights the unique contribution of this paper.

**Table 1.** Background summary of environmental efficiency evaluation of EVs using the LCA model.

| | Research Boundary | | | Research Features | Regional Comparison | Method Combination |
|---|---|---|---|---|---|---|
| | Environment | Economic | Social | | | |
| Liu et al., 2020 [52] | √ | | | Vehicle size and driving condition | | |
| Qiao et al., 2020 [53] | √ | √ | | Country comparison | | |
| Ren et al., 2020 [54] | √ | | | Hydrogen production and usage | | |
| Wang et al., 2021 [33] | √ | | | Battery production | | |
| Wang et al., 2019 [55] | √ | √ | √ | TOPSIS | | Multicriteria decision-making |
| Gan et al., 2020 [10] | √ | | | Temperature and energy exchange | √ | |
| This study | √ | | | Region and time differences | √ | SBM-DEA |

TOPSIS—technique for order preference by similarity to ideal solution.

## 3. Material and Methods

On the basis of the literature review, in this study, a framework is constructed to optimize the evaluation of the environmental efficiency of vehicles in different provinces, and a new metric is constructed. The framework contains four types of academic effort: (a) energy extraction, processing and transportation with updated data and more details; (b) characterization of external temperature of vehicles during operation; (c) characterization of the driving conditions of vehicles during operation; (d) alternative models of LCA and DEA for efficiency/inefficiency measurement.

### *3.1. Research Scope*

We developed a research framework and flowchart (see Figure 1) that summarizes this research concisely, so as to clearly state the scope, process and indicators designed for this research. According to the flow chart in Figure 1, the whole WTW is divided into two stages: WTT and TTW. In the WTT stage, we mainly consider the energy production of China's provinces, especially the processes of crude oil, coal, natural gas and electricity, and gradually analyze the environmental efficiency impacts brought by different energy indicators according to the process shown in Figure 1. In the TTW stage, we consider 4 kinds of vehicle and the temperature change and congestion conditions faced by the vehicle during operation. The construction of temperature factors and congestion factors makes the measurement of vehicle environmental efficiency more realistic. Specially, vehicle production, maintenance and recovery stages are not considered at present.

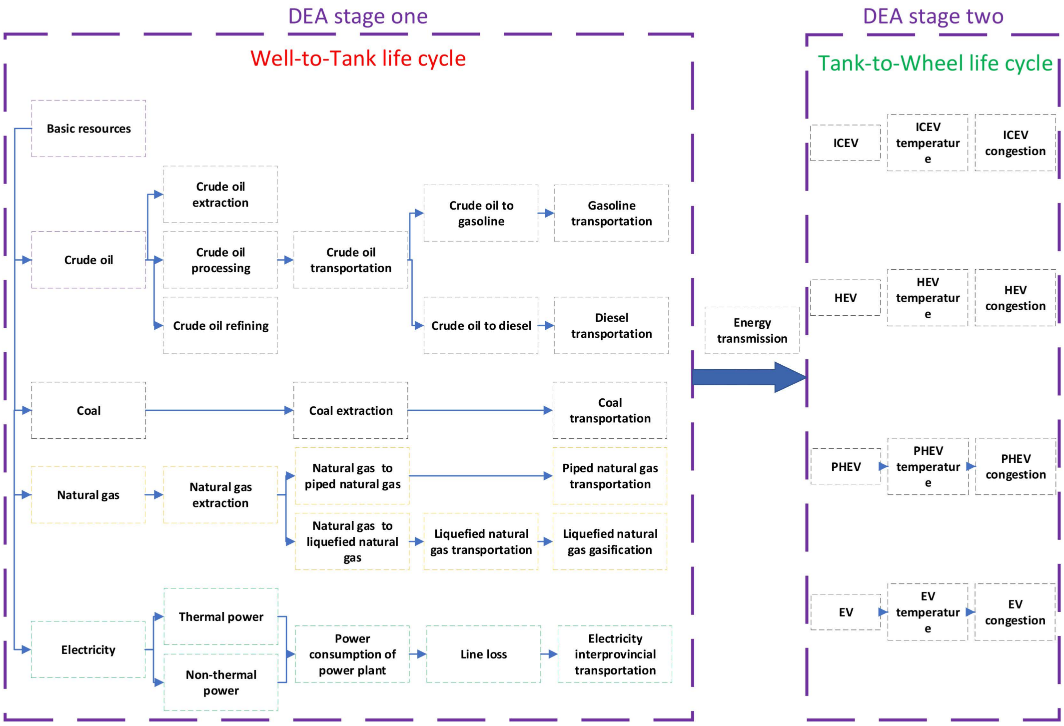


**Figure 1.** Research boundaries and flowchart.

On the basis of GREET2021, in this study, data from reliable sources published in Chinese journals and reports were utilized. GREET is an energy and materials extraction, transport and use model developed by Argonne National Laboratory to measure carbon and pollution emissions and technical efficiency, and constitutes a proven LCA environmental assessment tool for fuels and related materials used in the United States [10,56]. In particular, we determined the greenhouse gas coefficient of methane (CH4) to be 34 based on Recipe2016 data [57], which differs from the value of 30 reported by Gan [10] and the value of 25 reported by Masnadi [58]. The assumptions made for the calculation rested on stable economic and social conditions over the next century, as well as the need for human intervention to regulate the environment. Our findings are in agreement with the present and upcoming environmental and social conditions faced by the provinces in China.

### 3.2. *WTT: Energy Extraction, Processing and Transportation*

#### 3.2.1. Crude Oil and Fossil Products

Based on Chinese data from the China Energy Statistical Yearbook 2021 and the IEA 2019, we updated some basic energy data used in the GREET model. The updated data are shown in Table 2. The data related to ($E_{carbon}$) content and low heating value ($E_{low-heating}$) are taken from the China Energy Statistical Yearbook 2021 [59] and the IEA 2019 data for China [10,60]; we also changed the density ($\rho$) for crude oil, gasoline, diesel, kerosene and fuel oil, making them consistent with the real-life situation.

**Table 2.** China basic energy data (partial).

| Variety | Carbon Content (g C/MJ) | Low Heating Value (kJ/kg) | Density (g/cm$^3$) |
|---|---|---|---|
| Raw coal | 25.8 | 20,908 | No change |
| Cleaned coal | 26.7 | 26,344 | No change |
| Crude oil | 20.1 | 41,816 | 0.859 |
| Gasoline | 18.9 | 43,070 | 0.748 |
| Diesel | 20.2 | 42,652 | 0.858 |
| Kerosene | 19.6 | 43,070 | 0.793 |
| Fuel oil | 21.1 | 41,816 | 0.878 |
| Pet coke | 19.5 | No change | No change |
| LPG | 17.2 | 50,179 | No change |
| Coke | 29.4 | 28,435 | No change |
| Coke oven gas | 13.6 | 16,726 | No change |
| Coal tar | 22 | 33,453 | No change |
| Petroleum coal | 26.6 | No change | No change |
| Naphtha | 20 | No change | No change |
| Refinery gas | 15.7 | 45,998 | No change |
| Natural gas | 15.3 | 32,238 | No change |

LPG—liquefied petroleum gas.

On this basis, we further refined the extraction and transportation of crude oil, gasoline, diesel, natural gas and coal in China. Taking crude oil as an example, China imported 84% of its crude oil in 2021, as reported by the China Customs Administration. The top crude oil exporters to China were Saudi Arabia (17.07%), Russia (15.52%), Iraq (11.13%), Oman (8.73%) and Angola (7.63%). On the basis of Masnadi's research on carbon emissions of crude oil imports [58], we computed carbon emissions for each unit of crude oil imported by China. It was calculated that the recovery rate of oil shipped to China was 95.52% (in 2021). Additional materials used in processing petroleum include crude oil (0.1517 MJ/MJ), residual oil (0.008 MJ/MJ), diesel oil (0.0524 MJ/MJ), gasoline (0.0003 MJ/MJ), natural gas (0.6216 MJ/MJ), liquefied petroleum gas (0.0093 MJ/MJ) and electricity (0.1567 MJ/MJ), and the crude oil is transported by pipeline (kJ/t-km) and marine tankers (g fuel oil/kWh). We also took into account non-$CO_2$ emissions, which include on-site recovery and combustion of natural gas (0.85 g $CO_2$-eq/MJ) and oil extraction energy use (0.82 g $CO_2$-eq/MJ). The detailed data can be consulted in Supplementary Material S2, while the key information is provided in Table 3.

**Table 3.** China's carbon emissions per unit of energy.

| Variety | Carbon Dioxide Emission | Unit |
|---|---|---|
| Raw coal | 2.687 | g $CO_2$-eq/MJ |
| Crude oil | 5.326 | g $CO_2$-eq/MJ |
| Gasoline | 21.510 | g $CO_2$-eq/MJ |
| Diesel | 14.694 | g $CO_2$-eq/MJ |
| Fuel oil | 9.782 | g $CO_2$-eq/MJ |
| LNG | 7.754 | g $CO_2$-eq/MJ |
| Pet coke | 10.310 | g $CO_2$-eq/MJ |
| Natural gas | 7.609 | g $CO_2$-eq/MJ |
| Kerosene | 8.623 | g $CO_2$-eq/MJ |
| Electricity | 747.2 | g $CO_2$-eq/kWh |

LNG—liquefied natural gas.

Table 3 shows carbon emissions per unit of energy in China after receiving part of the localized data. These results do not include the regional characteristics broken down by province; that is to say, in this study, the crude oil and fossil products consumed by the petrochemical industry and automobile driving are uniform. We also assume that the electricity participating in the extraction, processing and transportation of crude oil and fossil products does not possess regional characteristics.

### 3.2.2. Provincial Electricity

Power Production and Loss in Provinces

We integrated three primary sources of data, including the China Energy Statistical Yearbook, 2021 [59], the China Power Industry Statistics, 2019 Compilation [61], and the China Electric Power Yearbook, 2019 [62]. Integrating these three sources allows the characterization of carbon emissions per unit of power production in different provinces, while taking into account varying factors such as power production, provincial line loss rate, plant power consumption rate, and inter-provincial electricity transportation. Taking the electricity generation of Shaanxi as an example, the contributions of thermal power, hydropower, wind power and solar power in 2019 were 84.84%, 7.07%, 3.81% and 4.29%, respectively, and Shaanxi has no nuclear energy. With respect to Shaanxi's thermal power, coal-fired power plants accounted for 95.19%, gas-fired power plants accounted for 0.26%, and fuel oil, garbage, biomass and other thermal power stations accounted for 4.55%. At the same time, Shaanxi's coal-fired power plants used 6.95% of the total electricity consumed for power plant operation, while hydropower plants, wind plants and solar power plants used 0.8%, 2.36% and 1.65%, respectively. The detailed data are provided in Supplementary Material S2.

The key data regarding electricity production for each province in 2020 are summarized in Table 4, including the power production and the line loss for power production, which was replaced using GREET [59]. In this paper, we also account for varied line loss rates produced by distinct power facilities in each province [61]. Additionally, the plant's electricity consumption in power production is also under consideration [61–63]. To simplify data, we classified the plant electricity consumption rate of oil and garbage power generation as the electricity consumption rate of the coal power plant, while the electricity consumption rate of a biomass power plant was classified as the electricity consumption rate of a natural gas power plant. Furthermore, the missing data for each province were replaced with the national average.

**Table 4.** Total power production of each province.

| Province | Thermal Power ($10^8$ kWh) | Hydro Power ($10^8$ kWh) | Wind Power ($10^8$ kWh) | Solar Power ($10^8$ kWh) | Nuclear Power ($10^8$ kWh) | Line Loss (%) |
|---|---|---|---|---|---|---|
| Beijing | 52,201.49 | 10.19 | 3.41 | 4.77 | 3483.54 | 6.15 |
| Tianjin | 445.71 | 0.12 | 10.83 | 15.43 | 0.00 | 6.3 |
| Hebei | 706.6 | 16.44 | 317.66 | 176.31 | 0.00 | 6.39 |
| Shanxi | 2787.25 | 49.07 | 224.3 | 127.5 | 0.00 | 5.5 |
| Neimenggu | 2960.8 | 58.07 | 665.8 | 162.8 | 0.00 | 3.71 |
| Liaoning | 4608.41 | 43.58 | 183.09 | 42.23 | 0.00 | 5.67 |
| Jilin | 1476.74 | 66.76 | 114.62 | 39.76 | 327.3 | 7.21 |
| Heilongjiang | 725.24 | 27.71 | 139.95 | 32.44 | 0.00 | 8.7 |
| Shanghai | 911.73 | 0.00 | 16.91 | 7.77 | 0.00 | 2.23 |
| Jiangsu | 797.45 | 30.76 | 183.89 | 154.07 | 0.00 | 3.34 |
| Zhejiang | 4468.81 | 256.58 | 32.61 | 118.99 | 328.89 | 3.79 |
| Anhui | 2500.95 | 51.09 | 46.96 | 124.66 | 628.52 | 6.7 |
| Fujian | 2663.97 | 442.35 | 87.27 | 15.94 | 0.00 | 3.65 |
| Jiangxi | 1411.24 | 167.74 | 51.3 | 55.9 | 621.17 | 6.37 |
| Shandong | 1100.96 | 5.23 | 224.99 | 166.9 | 0.00 | 5.53 |
| Henan | 5292.91 | 145.06 | 87.99 | 101.75 | 207.2 | 7.55 |
| Hubei | 2553.5 | 1356.98 | 73.83 | 56.76 | 0.00 | 6.63 |
| Hunan | 1469.94 | 543.97 | 74.98 | 25.87 | 0.00 | 7.96 |
| Guangdong | 914.6 | 391.01 | 71 | 53.4 | 0.00 | 3.87 |
| Guangxi | 3433.89 | 593.41 | 61.33 | 13.49 | 1101.73 | 5.09 |

**Table 4.** *Cont.*

| Province | Thermal Power ($10^8$ kWh) | Hydro Power ($10^8$ kWh) | Wind Power ($10^8$ kWh) | Solar Power ($10^8$ kWh) | Nuclear Power ($10^8$ kWh) | Line Loss (%) |
|---|---|---|---|---|---|---|
| Hainan | 1006.51 | 17.27 | 4.75 | 14 | 171.53 | 6.02 |
| Chongqing | 212.46 | 242.27 | 11.02 | 3.33 | 97.2 | 5.15 |
| Sichuan | 554.93 | 3316.01 | 71.25 | 28.15 | 0.00 | 7.78 |
| Guizhou | 508.47 | 769.36 | 78.05 | 19.6 | 0.00 | 4.69 |
| Yunnan | 1339.53 | 2855.85 | 245.29 | 48.18 | 0.00 | 4.2 |
| Shaanxi | 3.88 | 68.49 | 83.62 | 94.15 | 0.00 | 5.9 |
| Gansu | 1860.45 | 154.98 | 228.11 | 118.44 | 0.00 | 6.3 |
| Qinghai | 787.82 | 496.12 | 66.49 | 158.24 | 0.00 | 3.7 |
| Ningxia | 107.37 | 554.04 | 185.55 | 114.69 | 0.00 | 3.5 |
| Xinjiang | 1443.87 | 21.87 | 413.3 | 136 | 0.00 | 7.85 |

Inter-Provincial Transport

China's power system infrastructure is well established, and inter-provincial power transmission is widespread [64]. Accounting for inter-provincial power transportation when calculating carbon emissions is consistent with the current situation. Based on data compiled by the China Electricity Council in 2019 [61], we calculated the power transmission among the provinces.

We divided North China, Central China, Southwest China and Northwest China into provinces according to China's regional division rules. Moreover, we expanded some power transportation lines for inter-provincial transportation. Next, to determine the power supply to each province in the region, we calculated the proportion of total power consumption for each province. Finally, we calculated the actual unit electricity carbon emissions in each province based on inter-provincial electricity transportation. For example, Hebei transported 48.772294 billion kWh of electricity to North China in 2019, which includes Beijing, Tianjin, Shandong, Shanxi and Neimenggu. The total electricity consumption in North China is 1552.722 billion kWh, while that in Beijing is 111.4022 billion kWh. Hence, Hebei transported 3.58157 billion kWh of electricity to Beijing. Finally, the amount of electricity supplied by Hebei was calculated according to the line loss rate of Hebei, not the power consumption of the province.

Table 5 shows the results of carbon emissions per unit of power in different regions based on localized GREET data. The provinces that do not consider electricity transmission have $CO_2$ emissions in the second column, and the provinces that do consider electricity transmission have $CO_2$ emissions in the third column. The gap in $CO_2$ emissions arises when electricity transmission is taken into account (column 4), and considering power transmission is more realistic. Detailed data can be found in Supplementary Materials S2 and S3.

**Table 5.** Unit electricity carbon emissions for each province.

| Province | Carbon Dioxide Emission (without Transmission) | Carbon Dioxide Emission (with Transmission) | Difference | Unit |
|---|---|---|---|---|
| Beijing | 161.3 | 206.5 | 45.2 | g $CO_2$-eq/MJ |
| Tianjin | 247.1 | 242.0 | −5.1 | g $CO_2$-eq/MJ |
| Hebei | 228.7 | 231.0 | 2.3 | g $CO_2$-eq/MJ |
| Shanxi | 241.3 | 240.4 | −0.9 | g $CO_2$-eq/MJ |
| Neimenggu | 237.1 | 236.7 | −0.4 | g $CO_2$-eq/MJ |
| Liaoning | 195.7 | 205.1 | 9.4 | g $CO_2$-eq/MJ |
| Jilin | 201.3 | 203.0 | 1.7 | g $CO_2$-eq/MJ |
| Heilongjiang | 212.9 | 212.9 | 0.0 | g $CO_2$-eq/MJ |
| Shanghai | 221.8 | 170.6 | −51.2 | g $CO_2$-eq/MJ |

**Table 5.** *Cont.*

| Province | Carbon Dioxide Emission (without Transmission) | Carbon Dioxide Emission (with Transmission) | Difference | Unit |
|---|---|---|---|---|
| Jiangsu | 209.2 | 201.3 | −7.9 | g $CO_2$-eq/MJ |
| Zhejiang | 172.6 | 171.6 | −1.0 | g $CO_2$-eq/MJ |
| Anhui | 236.3 | 235.0 | −1.3 | g $CO_2$-eq/MJ |
| Fujian | 135.1 | 135.1 | 0.0. | g $CO_2$-eq/MJ |
| Jiangxi | 194.7 | 188.1 | −6.6 | g $CO_2$-eq/MJ |
| Shandong | 243.1 | 239.2 | −3.9 | g $CO_2$-eq/MJ |
| Henan | 244.9 | 238.5 | −6.4 | g $CO_2$-eq/MJ |
| Hubei | 129.0 | 133.1 | 4.1 | g $CO_2$-eq/MJ |
| Hunan | 143.5 | 149.2 | 5.7 | g $CO_2$-eq/MJ |
| Guangdong | 162.9 | 138.5 | −24.4 | g $CO_2$-eq/MJ |
| Guangxi | 125.7 | 124.0 | −1.7 | g $CO_2$-eq/MJ |
| Hainan | 142.6 | 143.6 | 1.0 | g $CO_2$-eq/MJ |
| Chongqing | 171.4 | 134.1 | −37.3 | g $CO_2$-eq/MJ |
| Sichuan | 26.5 | 31.6 | 5.1 | g $CO_2$-eq/MJ |
| Guizhou | 172.8 | 172.8 | 0.0 | g $CO_2$-eq/MJ |
| Yunnan | 18.4 | 18.36 | −0.04 | g $CO_2$-eq/MJ |
| Shaanxi | 234.2 | 223.6 | −10.6 | g $CO_2$-eq/MJ |
| Gansu | 134.6 | 129.2 | −5.4 | g $CO_2$-eq/MJ |
| Qinghai | 32.7 | 39.7 | 7.0 | g $CO_2$-eq/MJ |
| Ningxia | 223.3 | 209.2 | −14.1 | g $CO_2$-eq/MJ |
| Xinjiang | 227.6 | 227.2 | −0.4 | g $CO_2$-eq/MJ |

### *3.3. TTW: Vehicle Operation*

#### 3.3.1. Vehicle Performance

It is critical to use vehicles of the same size and performance, but with different powertrains [10,65]. In this study, we adopted Gan's authoritative research results on Chinese vehicles with different power systems [10], as shown in Table 6, and energy consumption data are ideal data without any interference. The models used in this study were ordinary sedan models, while mini vehicles, SUVs and multi-purpose vehicles (MPVs) were excluded. Specifically, the study examined the life-cycle ratio of the charge-sustaining (CS) mode and the charge-depleting (CD) mode of PHEVs, referred to as the utility factor (UF). This study also employed the simulation results of Gan, namely, the reported UF value of 0.62, which means that in the entire life cycle of PHEVs, 62% of mileage is driven by electric motors and 38% is driven by internal combustion engines [10].

**Table 6.** Average vehicle performance in China.

| Vehicle Model | Mass (kg) | Labeled FCR (L/100 km) | Labeled ECR (kW h/100 km) | TTW Consumption (MJ/km) |
|---|---|---|---|---|
| ICEV | 1444 | 6.7 | Unavailable | 2.68 |
| HEV | 1518 | 4.3 | Unavailable | 1.72 |
| EV | 1518 | Unavailable | 16.4 | 1.19 |
| PHEV | 1694 | CS: 5.0 (62%) | CD: 21.5 (38%) | 2.39 |

FCR—fuel consumption rate, ECR—electricity consumption rate.

Internal combustion engines do not rely solely on gasoline as their fuel source because biomass gasoline and natural gas can also substitute for gasoline and offer greater ecological advantages [66]. To emphasize the complexity of the energy sources of ICEVs, we selected data for gasoline, fuel oil, natural gas and liquefied natural gas in the China Energy Statistical Yearbook 2021 [59] from "transportation, storage and postal industry". Diesel and kerosene were not selected because they are more commonly used in large vehicles in China. Taking Beijing as an example, Beijing consumed 673,600 tons of gasoline, 150 tons of fuel oil, 281 million cubic meters of natural gas and 1619 billion cubic meters of liquefied natural gas in automobiles in 2019. According to the calculation of emission and calorific value performed on the basis of the fuel production data and weighted average, the emissions of ICEs in Beijing were 22.197 g $CO_2$-eq/MJ. Table 7 shows the fuel sources used by ordinary sedan models and carbon emissions per unit of energy use after fuel combination, among which the average value for China is 22.419 g $CO_2$-eq/MJ.

**Table 7.** Total vehicle energy consumption and weighted carbon emissions in each province.

| Province | Gasoline ($10^4$ t) | Fuel Oil ($10^4$ t) | Natural Gas ($10^8$ $m^3$) | LNG ($10^8$ $m^3$) | ICE Emission (g $CO_2$-eq/MJ) |
|---|---|---|---|---|---|
| Beijing | 67.36 | 0.015 | 2.81 | 16.19 | 22.197 |
| Tianjin | 97.51 | 28.54 | 3.51 | 0.00 | 21.421 |
| Hebei | 304.22 | 13.08 | 1.82 | 101.45 | 22.706 |
| Shanxi | 231.38 | 0.00 | 9.96 | 0.00 | 22.808 |
| Neimenggu | 133.96 | 0.02 | 9.99 | 27.33 | 21.552 |
| Liaoning | 674.54 | 109.34 | 7.52 | 0.00 | 22.799 |
| Jilin | 217.62 | 0.00 | 6.89 | 0.00 | 23.191 |
| Heilongjiang | 79.01 | 0.00 | 6.56 | 2.20 | 21.723 |
| Shanghai | 197.93 | 625.29 | 1.31 | 0.00 | 16.460 |
| Jiangsu | 643.17 | 91.22 | 14.84 | 4.89 | 22.525 |
| Zhejiang | 272.5 | 99.30 | 0.02 | 0.00 | 21.891 |
| Anhui | 419.23 | 14.50 | 3.08 | 0.00 | 23.909 |
| Fujian | 283.36 | 112.03 | 2.06 | 0.00 | 21.550 |
| Jiangxi | 375.00 | 2.80 | 0.80 | 0.00 | 24.406 |
| Shandong | 773.58 | 26.97 | 8.80 | 3.78 | 23.708 |
| Henan | 693.24 | 1.08 | 9.42 | 0.00 | 23.905 |
| Hubei | 489.84 | 105.99 | 5.20 | 0.00 | 22.466 |
| Hunan | 477.35 | 67.20 | 3.25 | 0.00 | 23.101 |
| Guangdong | 1056.91 | 205.72 | 1.49 | 0.00 | 22.914 |
| Guangxi | 256.03 | 3.17 | 5.65 | 0.00 | 23.462 |
| Hainan | 33.82 | 34.98 | 0.83 | 0.00 | 19.122 |
| Chongqing | 246.10 | 11.55 | 6.99 | 10.28 | 22.852 |
| Sichuan | 490.81 | 0.68 | 80.20 | 74.82 | 20.374 |
| Guizhou | 245.50 | 0.00 | 3.42 | 4.53 | 23.825 |
| Yunnan | 515.76 | 0.01 | 0.17 | 0.32 | 24.570 |
| Shaanxi | 168.62 | 1.89 | 3.63 | 91.88 | 21.925 |
| Gansu | 188.30 | 0.00 | 4.85 | 0.00 | 23.410 |
| Qinghai | 84.78 | 0.00 | 5.52 | 0.00 | 22.190 |
| Ningxia | 82.50 | 0.00 | 2.69 | 0.60 | 23.133 |
| Xinjiang | 341.82 | 0.00 | 7.94 | 0.05 | 23.509 |

### 3.3.2. The Impact of Temperature

Compared with ICEVs, EVs perform worse under extreme ambient temperature, requiring more maintenance and higher energy consumption to ensure normal operation [11]. Moreover, China's geographical location and provincial distribution determine that different provinces have different climates and average temperatures. To simulate the different climates in different provinces, Wu's study on the relationship between temperature factor and energy consumption in ICEVs, HEVs, PHEVs and EVs at the TTW stage was referenced in this study [11]. We followed Wu's research and used the 12-month average temperature of each province in 2021 as the environment temperature (China State Statistics Bureau, 2021). The relationship between environmental temperature and energy consumption is shown in Equation (1):

$$r_T = \begin{cases} (T - 23.9) * a_1 + 1 & T > 23.9\,^{\circ}C \\ 1 & 15.5\,^{\circ}C \le T \le 23.9\,^{\circ}C \\ (15.5 - T) * a_2 + 1 & 15.5\,^{\circ}C \ge T \end{cases} \tag{1}$$

where $r_T$ is the energy consumption rate, which is the temperature factor employed in this work, $T$ is the actual temperature that vehicle faces during its life cycle, in degrees Celsius, $a_1$ is the high-temperature factor, with values of 0.0129, 0.0171, 0.0183 and 0.0210, respectively, for ICEVs, HEVs, PHEVs and EVs, while conversely, $a_2$ is the low-temperature factor, with values of 0.0064, 0.0123, 0.0154 and 0.0242, respectively, for ICEVs, HEVs, PHEVs and EVs. The specific temperature coefficients of each type of vehicle in each province are shown in Figure 2, and the detailed data are shown in Table S1 of Supplementary Material S1.

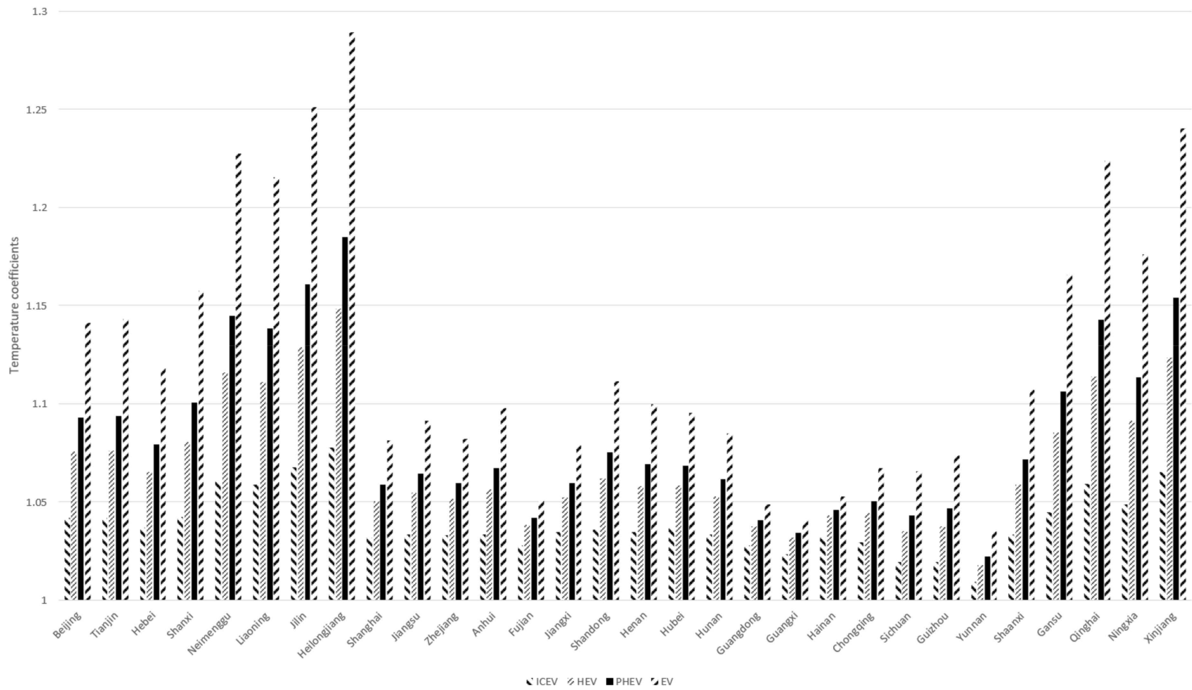


**Figure 2.** Temperature coefficients of four types of vehicle in different regions.

### 3.3.3. The Impact of Congestion

Urban and rural roads exhibit considerable disparities in vehicle performance [39,67], which are fundamentally a result of the conditions of the roads and other factors associated with speed [68–70]. This section outlines the methodology utilized to replicate driving conditions in distinct regions. This was achieved by analyzing statistical data on vehicle operating behavior statistics, driving speed fitting, driving energy consumption estimation and travel preference simulation. Subsequently, we computed the driving energy consumption coefficients of four vehicle types in various provinces. This factor is designated as the congestion factor, which captures regional and time differences.

First, we need to find the approximate speed of each car when it is traveling in different provinces. The Baidu Congestion Index platform is a reliable data platform that detects congestion and traffic speed of urban and expressway roads using real-time Baidu Map data. To simulate vehicle operating behaviors in the face of different congestion and road conditions in different provinces, we first took data in October 2021 as the benchmark, counted the congestion index of 100 major congested cities every 5 min from Baidu's congestion index platform, and counted 57,600 congestion indexes on working days and non-working days. Then, the congestion index and driving speed data of 6000 provincial capitals were selected for curve fitting. The results are shown in Figure 3, and fitting conditions are shown in Tables 8 and 9. These results show that the relationship between congestion index and travel speed is closest to exponential function, whose $R^2$ is 0.714. As can be seen from the results, when the congestion index is 1, the average speed of driving without congestion is 48.96 km/h. By using this function, the speed and the congestion of vehicles in a certain area of a city at a certain time can be calculated. For specific congestion data and replacement values, see Supporting Material S4 for details.

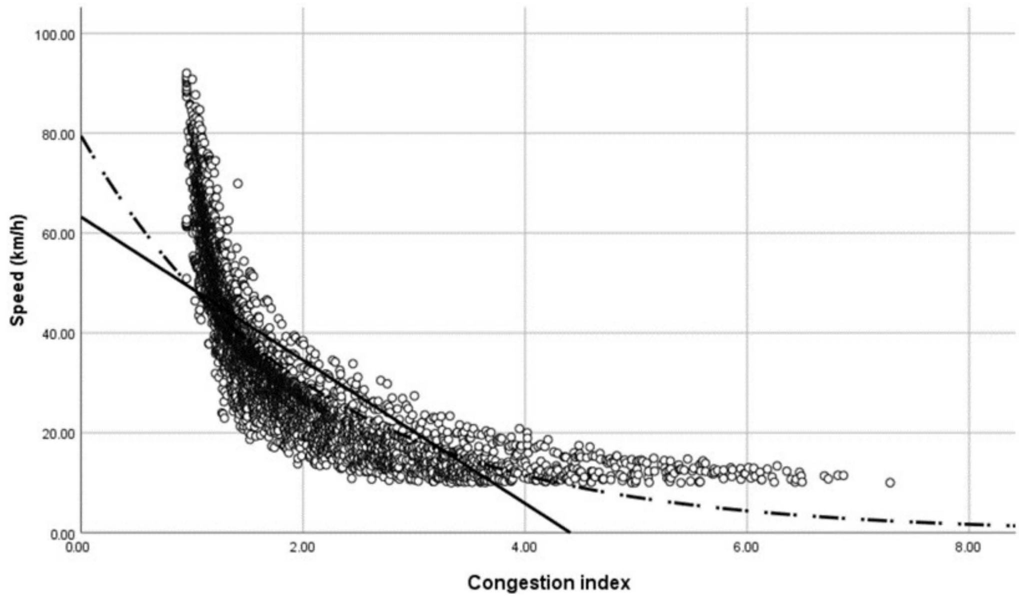


**Figure 3.** Congestion index–speed fitting function.

**Table 8.** Congestion index–speed fitting results.

| Model | Variables | B | Standard Error | Beta | t | Significance |
|---|---|---|---|---|---|---|
| Linear | Congestion index | −14.347 | 0.175 | −0.742 | −82.199 | 0.000 |
| | (Constant) | 63.223 | 0.356 | | 177.596 | 0.000 |
| Exponent | Congestion index | −0.484 | 0.004 | −0.845 | −117.367 | 0.000 |
| | (Constant) | 79.443 | 0.668 | | 118.960 | 0.000 |

**Table 9.** Congestion index–speed coefficient R.

| Model | R | $R^2$ | Adjusted $R^2$ | Error in Standard Estimation |
|---|---|---|---|---|
| Linear | 0.742 | 0.550 | 0.550 | 11.588 |
| Exponent | 0.845 | 0.714 | 0.713 | 0.274 |

The energy consumption of EVs and ICEVs depends on speed. EVs are better suited for low-speed environments, while ICEVs are more suitable for high-speed environments [40]. Thus, it can be inferred that the energy consumption of EVs and ICEVs depends on speed. To further estimate the driving energy consumption of vehicles, we discuss EVs separately from ICEVs. The energy consumption curve of ICEVs can be fitted into a speed-related sixth power curve [71], in which the energy consumption of ICEVs is the lowest when speed is 63.78 km/h. This curve was used to simulate the energy consumption of ICEVs, HEVs and CD mode in PHEVs. In contrast, according to Asamer's research, the energy consumption of EVs is better at low speed and can be reduced at ultra-high speed [40]. To discover the relationship between the speed and energy consumption of EVs and draw a comparison with ICEVs [71], we extracted the research data of Asamer [40] and conducted curve fitting (see Figure 4). The fitting situation is shown in Tables 10 and 11. It can be seen that the speed–energy consumption curve of EVs can be fitted into a speed-related cubic curve for which the $R^2$ is 0.166. Based on the function fitting results, the minimum energy consumption of EVs occurs at a speed of 37.95 km/h. This curve was used to estimate the energy consumption of CS mode in PHEVs and EVs. This gives an idea of the approximate energy consumption of the vehicle at different speeds.

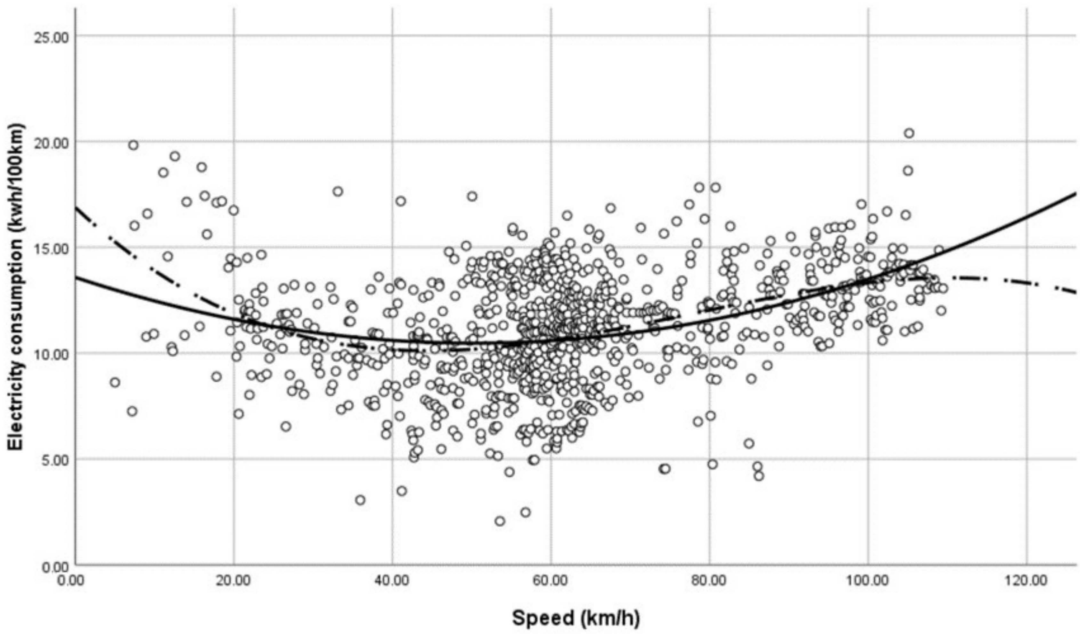


**Figure 4.** EV speed–energy consumption fitting function.

**Table 10.** EV speed–energy consumption fitting results.

| Model | Variables | B | Standard Error | Beta | t | Significance |
|---|---|---|---|---|---|---|
| Two stages | Speed | −0.123 | 0.016 | −0.992 | −7.476 | 0.000 |
| | $Speed^2$ | 0.001 | 0.000 | 1.279 | 9.637 | 0.000 |
| | (Constant) | 13.576 | 0.511 | | 26.582 | 0.000 |
| Three stages | Speed | −0.352 | 0.054 | −2.832 | −6.509 | 0.000 |
| | $Speed^2$ | 0.006 | 0.001 | 5.798 | 5.644 | 0.000 |
| | $Speed^3$ | $-2.393 \times 10^{-5}$ | 0.000 | −2.763 | −4.435 | 0.000 |
| | (Constant) | 16.879 | 0.900 | | 18.750 | 0.000 |

**Table 11.** EV speed–energy consumption coefficient R.

| Model | R | $R^2$ | Adjusted $R^2$ | Error in Standard Estimation |
|---|---|---|---|---|
| Two stages | 0.386 | 0.149 | 0.147 | 2.500 |
| Three stages | 0.408 | 0.166 | 0.164 | 2.475 |

However, cars travel at different speeds at different times of the day because drivers have driving preferences. It is important to consider that the drivers' travel preferences vary in each period; thus, the percentage of vehicle operation differs [72,73]. To simulate drivers' travel preferences in a certain period, we followed Wang's study on the relationship between speed and travel intensity [74]. Equation (2) represents the fitting function for travel preference–speed:

$$\overline{V}_s(\overline{\rho}_s, \gamma) = \overline{V}_f * exp\left\{-\frac{1}{a}\left[\frac{\overline{\rho}_s(1+\gamma)}{\rho_m}\right]^b\right\} \tag{2}$$

where $\overline{V}_s$ represents the actual speed, $\overline{V}_f$ represents traffic converging to zero speed harmonic mean, $\overline{\rho}_s$ is the average flow, $\rho_m$ is the optimal flow, $a$ and $b$ are correlation coefficients, and $\gamma$ is the traffic standard deviation. According to the research of Wang, the relationship between $\gamma$ and $\overline{\rho}_s$ is $\gamma = 2.14\overline{\rho}_s - 29.317$, and Wang chose the road of Qingdao and congestion data as a case study ($a = -0.6756$, $b = 0.069$, $\rho_m = -28$, $\overline{V}_f = 46.96$). We update $\overline{V}_s$ in Equation (2) as $\overline{V}_f = 97.12$ and retain the values of $a$, $b$ and $\rho_m$; the travel preference–speed function across China is then as shown in Equation (3):

$$\overline{V}_s(\overline{\rho}_s) = 97.12 * exp\left\{-\frac{1}{-0.6756}\left[\frac{\overline{\rho}_s(2.14\overline{\rho}_s - 28.317)}{-28}\right]^{0.069}\right\} \tag{3}$$

Through the above calculation, we get the driving speed and driving energy consumption of the vehicle in a day, which can be expressed by the congestion coefficient. In summary, the congestion coefficient of a city on a given day is the ratio of actual energy consumption to the minimum energy consumption multiplied by travel preference for each time period. Nevertheless, the data collected and the congestion coefficient obtained are based on cities and the congestion coefficient of each province needs to be calculated according to the weighting of car ownership in each city. We assume that non-congested cities, which are not shown on the list of 100 major congested cities, have the lowest congestion coefficients, corresponding to 1.111 for ICEVs, HEVs and the CD mode for PHEVs and 1.008 for EVs and the CS mode for PHEVs on weekdays, and 1.103 for ICEVs, HEVs and the CD mode for PHEVs and 1.004 for EVs and the CS mode for PHEVs on non-weekdays. For details, see Supplementary Material S4. After calculation, the specific congestion coefficients of each type of vehicle in each province are shown in Figure 5 and Table S2 (see Supplementary Material S1) in greater details.

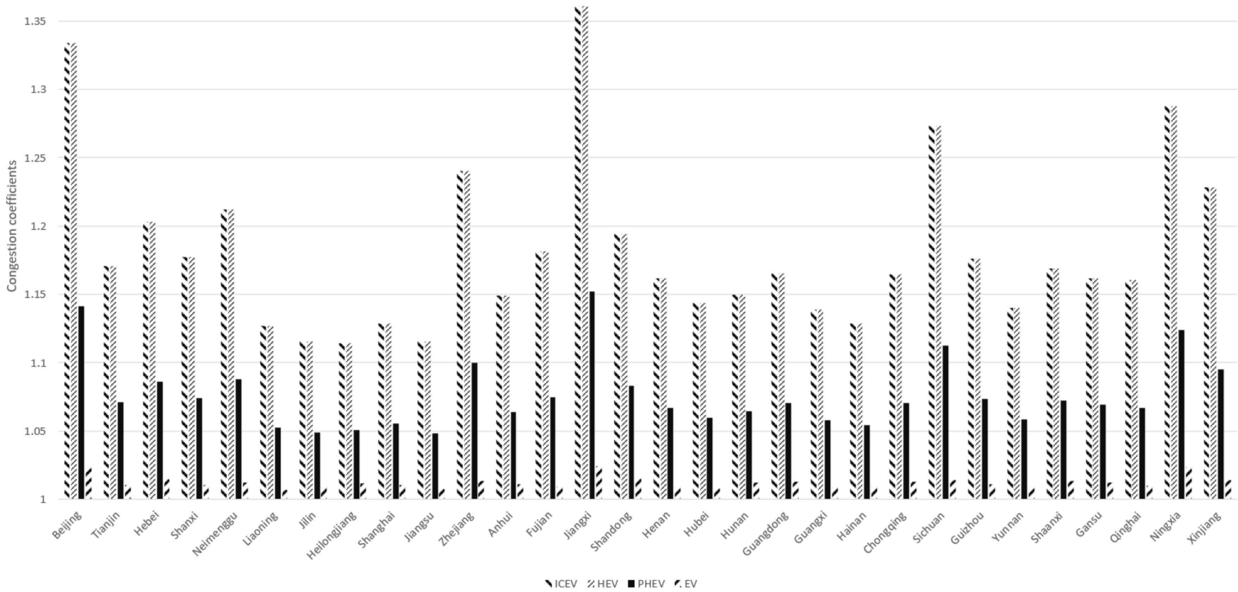


**Figure 5.** The congestion coefficients of four types of vehicle in different regions.

Figures 6 and 7 show the composition of the carbon emissions produced by ICEVs and EVs, respectively, in Beijing during the WTW stage. In Figures 6 and 7, WTT and TTW represent the basic carbon emissions of vehicles during the energy production stage and the energy consumption stage, respectively, while carbon emissions affected by the temperature coefficient and the congestion coefficient are not interdependent. Figures 6 and 7 show that the additional carbon emissions produced by ICEVs as a result of congestion in Beijing are much greater than the impact of congestion on EVs, while the climate in Beijing makes it necessary for EVs to emit more carbon dioxide during their whole life cycle in order to ensure normal operation.

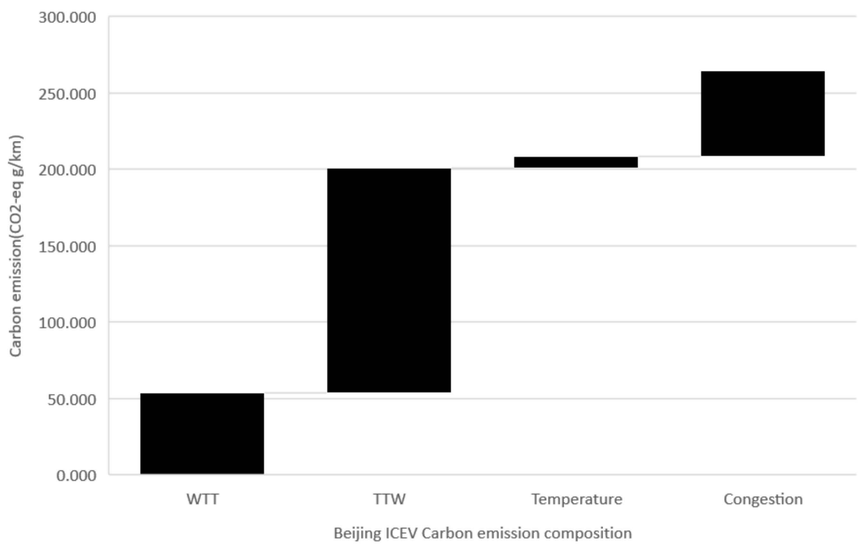


**Figure 6.** ICEV carbon emissions composition in Beijing.

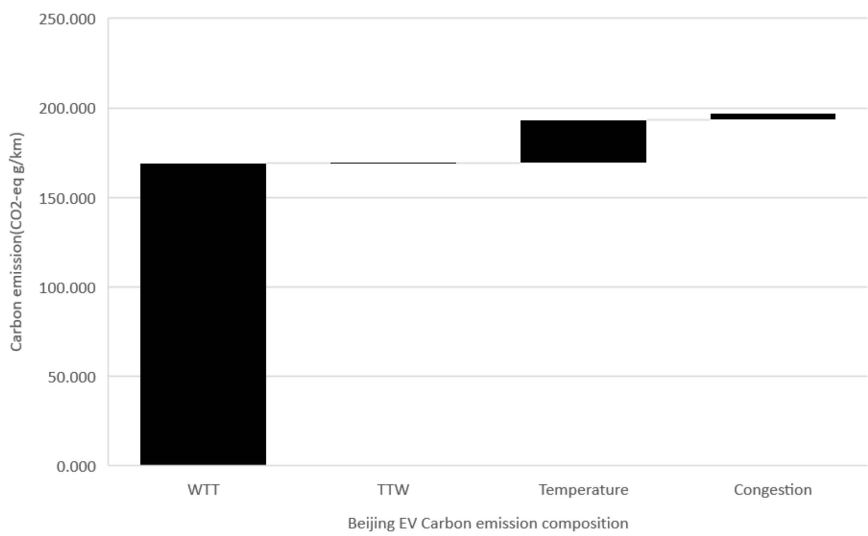


**Figure 7.** EV carbon emissions composition in Beijing.

### 3.4. Two-Stage SBM-DEA Model

On the basis of the studies of the two-stage DEA model [75–77], we believe that the WTT and TTW stages correspond to the two stages of DEA; Tone proposed the SBM model to solve the issue of inaccurate radial optimization in the traditional CCR model [78]. Thus, in this study, we construct a two-stage SBM-DEA model in which TTW serves as the main model.

We assume that for each DMU $(j = 1, 2, \ldots, n)$, there are $m_1$ input variables $x^1_{u0}$ $(u = 1, 2, \ldots, m_1)$ and $k$ intermediate output variables $z_{r0}$ $(r = 1, 2, \ldots, k)$, where the output variable of WTT is also the input variable of TTW. The SBM model of a DMU in the WTT stage is shown in Equations (4) to (8):

$$Min\ \rho_1 = T^1 - \frac{1}{m_1} \sum_{u=1}^{m_1} \frac{S^1_u}{x^1_{u0}} \tag{4}$$

$$T^1 + \frac{1}{k} \sum_{r=1}^{k} \frac{\tau^1_r}{z_{r0}} = 1 \tag{5}$$

$$\sum_{j=1}^{n} \Lambda^1_j x^1_{uj} + S^1_u = T^1 x^1_{u0} \quad u = 1, 2, \ldots, m_1 \tag{6}$$

$$\sum_{j=1}^{n} \Lambda_j^1 z_{rj} - \tau_r^1 = T^1 z_{r0} \quad r = 1, 2, \ldots, k \tag{7}$$

$$T^1, \Lambda_j^1, S_u^1, \tau_r^1 \geq 0 \tag{8}$$

where $\rho_1$ is the WTT stage efficiency of the DMU, $T^1$ is the efficiency multiplier that guarantees the establishment of Formula (2), $x_{u0}^1$ and $z_{r0}$ are actual data of the DMU, $\Lambda_j^1$ is the unit weight of unit $j$ in WTT stage, and $S_u^1$ and $\tau_r^1$ are the relaxation variables of the input $u$ and intermediate output variables $r$. If $\rho_1$ is 1, the DMU is in the best state at the WTT stage.

Affected by the WTT stage, the intermediate output variable will change. TTW at the optimal efficiency of WTT at $\rho_1$, $\tau_r^2$ will be affected by the regulating variable $\tau_r^1$. To depict this effect without affecting the calculation of linear model, we discretized the influence of $\tau_r^1$ on the TTW stage [77] and named this effect $\tau_r$, where $\tau_r = \tau_r^1 * a/10 (a = 0, 1, \ldots, 10)$. At this stage, there are $m_2$ input variables $x_{u0}^2 (u = 1, 2, \ldots, m_2)$, $k$ intermediate input variables $z_{rj}$ $(r = 1, 2, \ldots, k)$ and $q$ final output variables $y_{b0} (b = 1, 2, \ldots, q)$. The SBM model of the TTW stage affected by $\tau_r$ is shown as Equations (9) to (14):

$$Min\ \rho_2 = T^2 - \frac{1}{k+m_2} \left( \sum_{v=1}^{m_2} \frac{S_v^2}{x_{v0}^2} - \sum_{r=1}^{k} \frac{\tau_r^2 - a\frac{T^2}{T^1}\tau_r}{z_{r0}} \right) \tag{9}$$

$$T^2 + \frac{1}{q} \sum_{b=1}^{q} \frac{\mu_b}{y_{b0}} = 1 \tag{10}$$

$$\sum_{j=1}^{n} \Lambda_j^2 x_{vj}^2 + S_v^2 = T^2 x_{v0}^2 \quad v = 1, 2, \ldots, m_2 \tag{11}$$

$$\sum_{j=1}^{n} \Lambda_j^2 z_{rj} - \tau_r^2 + a\frac{T^2}{T^1}\tau_r = T^2 z_{r0} \quad r = 1, 2, \ldots, k \tag{12}$$

$$\sum_{j=1}^{n} \Lambda_j^2 y_{bj} - \mu_b = T^2 y_{b0} \quad b = 1, 2, \ldots, q \tag{13}$$

$$T^2, \Lambda_j^2, S_v^2, \tau_r^2, \mu_b \geq 0 \tag{14}$$

where $\rho_2$ is the efficiency of the TTW stage of the DMU, $T^2$ is the efficiency multiplier that guarantees the establishment of Formula (8), $x_{u0}^2$ and $z_{r0}$ are actual data of the DMU, and $\Lambda_j^2$ is the unit weight of $j$ unit in TTW stage. $S_v^2$, $\tau_r^2$ and $\mu_b$ are the relaxation variables of the $v$ second-stage input, the $r$ intermediate input variables and the $b$ second-stage output. Of these, the $z_{rj}$ property of the WTT stage and the TTW stage is the same, and the smaller the better.

The final WTW efficiency $\rho$ is obtained by multiplying the efficiency of the two WTT and TTW stages, as shown in Equation (15):

$$\rho = \rho_1 * \rho_2 \tag{15}$$

The selection of $x$indicators $_{u0}^1$, $x_{v0}^2$, $z_{r0}$ and $y_{b0}$ in the two-stage SBM-DEA model is shown in Figure 8, and detailed data can be seen in Tables S1–S4 (see Supplementary Material S1). In particular, the $z_{r0}$ of EVs does not include the emissions of internal combustion engines.

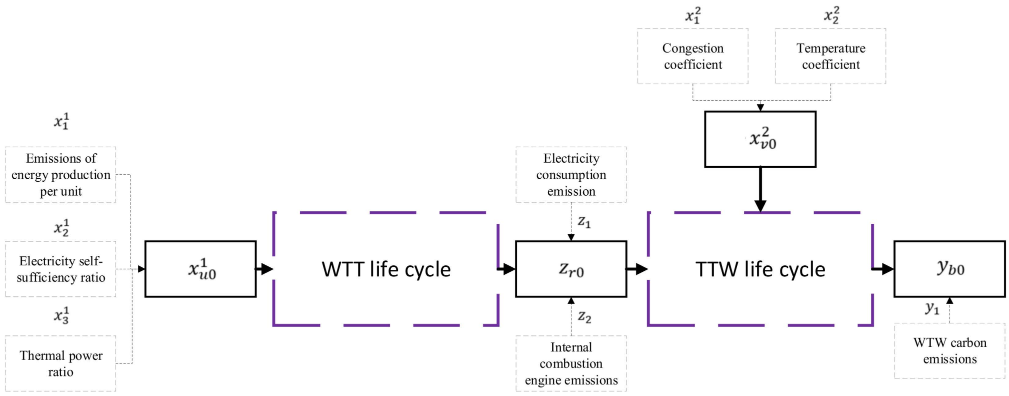


**Figure 8.** Indicator selection for the two-stage SBM-DEA model.

## 4. Results and Discussion

In this section, the results obtained from the LCA+DEA evaluation model are discussed. In Section 4.1, the efficiency results obtained in WTT are discussed, and in Section 4.2, the efficiency results obtained for WTT and WTW are discussed.

### 4.1. Provincial WTT-Stage Vehicle Environmental Efficiency

Based on previous research, the results for WTT-stage vehicles (divided into pure electric models and non-pure electric models) are shown in Tables S5 and S6 (see Supplementary Material S1), where each province's WTT efficiency is in the last column of the table. In the pure electric model, which only provides electricity, Fujian, Hubei, Guangxi and Hainan are less efficient because of the high carbon emissions per unit of energy production (98.358 $CO_2$-eq g/MJ, 103.228 $CO_2$-eq g/MJ, 83.226 $CO_2$-eq g/MJ and 62.510 $CO_2$-eq g/MJ, respectively). The provinces' optimization strategies are centered on the thermal power ratio and the electricity self-sufficiency ratio. For example, the Fujian and Hubei provinces mainly need to focus on the clean production of kerosene and diesel and reduce the proportion of thermal power generation, while Guangxi and Hainan provinces mainly need to improve their own power reliability.

In addition, we discovered an interesting phenomenon whereby, under the pure electric model, Beijing has a high efficiency with a high proportion of thermal power, low emissions due to energy production per unit, and the lowest electricity self-sufficiency ratio, while Sichuan, Yunnan and Qinghai have a low efficiency and a high electricity self-sufficiency ratio, a low proportion of thermal power, and low emissions due to energy production per unit. The efficiency of Yunnan is only 0.016. This phenomenon results from the high rate of electricity autonomy and the high proportion of hydropower generation. Clean energy is highly influenced by weather and climate [37,72], and the drought in the second half of 2022 caused a sharp decrease in power supply in Sichuan and Yunnan, which rely on hydroelectric power generation, and the resulting power gap was made up by power outages. Meanwhile, Shanghai, which relies on power from Sichuan, was not seriously affected due to the wide distribution of power sources. In addition, it can be seen from Table S5 (see Supplementary Material S1) that carbon emissions per unit of power consumption in Sichuan, Yunnan and Qinghai do not need to be optimized, indicating that, rather than reducing carbon emissions arising from power consumption, Sichuan, Yunnan and Qinghai should strengthen their inter-provincial power transmission or ensure the proportion of thermal power generation [37,79], thus improving the power toughness and ensuring that electricity generation will be gradually reduced when affected by environmental factors.

### 4.2. Provincial TTW-Stage Vehicle Environmental Efficiency

The model efficiency results of the TTW stage affected by the WTT stage are shown in Supplementary Material S5. We selected the most efficient result as the final result for the

TTW stage. Therefore, the optimization results of ICEVs, HEVs, PHEVs and EVs at the TTW stage with the highest efficiency are shown in Tables S7–S10 (see Supplementary Materials S1), respectively, where the EV model does not include intermediate input variable ICE emissions.

The low temperature during winter and spring in Heilongjiang, Liaoning and Jilin provinces has a great impact on the energy consumption of the four types of vehicle. Owing to its unique geographical location, Qinghai still has a great impact on the environment of three types of vehicle, with EVs being the exception. The reason the impact on EVs is not obvious is the low carbon emissions per unit of power consumption in Qinghai. While Neimenggu, Gansu and Xinjiang have less of an impact on the temperature of PHEVs and EVs than the three northeastern provinces, manufacturers still need their vehicles to pass stringent temperature tests, which are similar to those required by BYD, before launching their products in these regions.

The energy consumption of EVs in provinces does not increase significantly with higher traffic congestion, such as in the case of Ningxia, Qinghai and Beijing, because they are more efficient in low-speed environments. Therefore, not all provinces need to be concerned about the additional carbon emissions that result from EVs in congested areas. Beijing, Hebei, Zhejiang, Fujian, Guangdong, Chongqing, Sichuan, Guizhou, Ningxia and Xinjiang need to invest more resources into tackling congestion in order to reduce carbon emissions, but the factors are different. Beijing, Chongqing, Ningxia and Xinjiang are mainly due to the congestion of their capital cities and the large number of vehicles in capital cities, while Hebei, Zhejiang, Fujian, Guangdong and Guizhou have multiple congested cities within the province as a whole, and each congested city also has a certain number of vehicles.

Finally, we compared the total efficiency of four vehicle types in the WTW stage (see Figure 9) and compared WTW emissions before EV optimization in each province as the benchmark with those of ICEVs, HEVs and PHEVs in each province, as shown in Figure 10. The efficiency curves for ICEVs and HEVs are basically the same, but the efficiencies of Beijing, Shanghai, Zhejiang and Ningxia are lower than those for ICEVs and HEVs. This influence is caused by a multifaceted set of factors. The differences in temperature in ICEVs and HEVs result in differences in environmental efficiency in Liaoning, Jilin and Heilongjiang, while the difference in environmental efficiency in Shandong is due to congestion. Due to the combined influence of emissions due to electricity consumption and the temperature coefficient, the environmental efficiency of PHEVs and EVs in Jilin and Heilongjiang is not ideal. Moreover, Yunnan and Qinghai are not ideal due to the lower proportion of thermal power and the higher electricity self-sufficiency ratio. The main reason for these suboptimal results is that hydropower, like other clean power sources, is influenced by seasonal changes and the climate. To improve environmental efficiency, it is necessary to modify the hydropower ratios and electricity self-sufficiency ratios to increase resilience to electricity outages.

Contrary to the conclusions of Gan [10], we found that the WTW carbon emissions of an EV is basically lower than that of an ICEV (except in Heilongjiang Province), and the difference between EVs and ICEVs is affected by the energy composition and power composition of each province when taking the influence of temperature caused by climate and congestion caused by road conditions into consideration. Three factors contribute to this difference: (1) we updated the $CO_2$ coefficient of CH4 to 34 based on Recipe2017; (2) our data cover the years 2019–2021, while Gan's data were from before 2017; (3) we considered the impact of congestion on vehicle energy consumption and different fuel choices, whereas Gan's study only used gasoline as the fuel for ICEVs, HEVs and PHEVs.

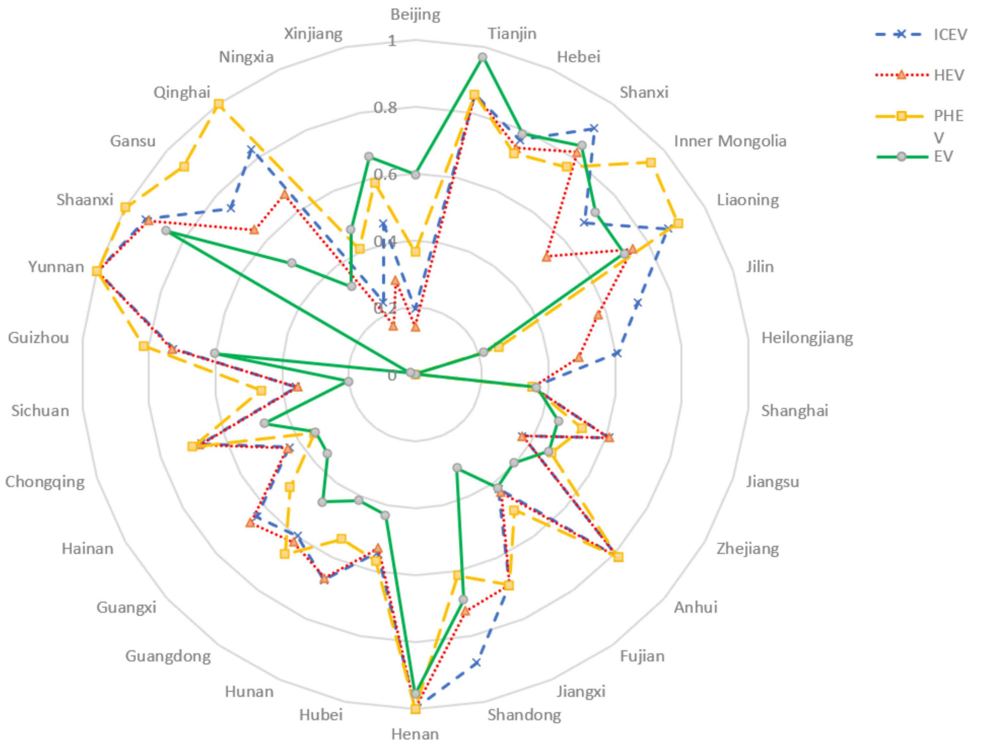


**Figure 9.** Provincial WTW efficiency of four types of vehicle.

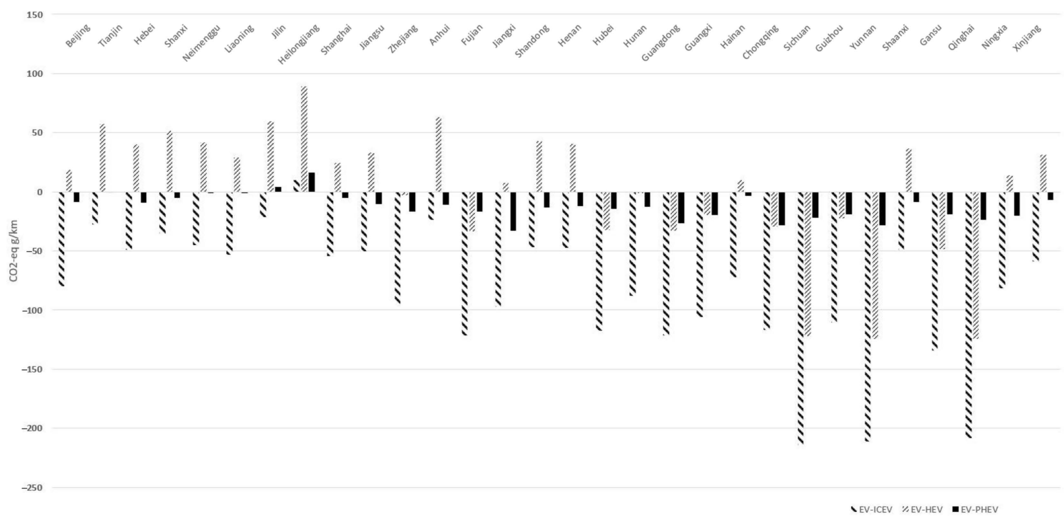


**Figure 10.** Provincial EV carbon emissions differences among different models.

## 5. Conclusions

In this study, the characteristics of provinces, including differences in fuel production, power production, inter-provincial power transportation and climate change, were considered. This study also constructed a new road congestion indicator that is able to simulate different road conditions at different times and in different regions. Moreover, we combined LCA and two-stage SBM-DEA models into a more realistic model in order to calculate the WTW carbon emissions and environmental efficiency of four types of vehicle in 30 provinces in China. We found that the WTW emission range of ICEVs was 288.28–217.40 $CO_2$-eq g/km, the WTW emission range of HEVs was 183.98–138.97 $CO_2$-eq g/km, and the WTW emission range was 231.70–55.17 $CO_2$-eq g/km for PHEVs and 248.20–26.67 $CO_2$-eq g/km for EVs. The WTW carbon emissions of EVs were generally lower than that of ICEVs (except in Heilongjiang Province).

On the basis of this research, the management implications at the provincial level can be summarized as follows. (1) While increasing the proportion of clean energy in electric power to significantly reduce carbon emissions, provinces should maintain a certain proportion of thermal power and inter-provincial power transmission to ensure power toughness and sustainability to prevent the occurrence of power shortage in the Yunnan-Guizhou Plateau in the second half of 2022. (2) The temperature coefficient mainly affects the environmental efficiency of PHEVs and EVs with motors as the power source. To minimize the effect of temperature on EVs, extreme temperature testing, especially extreme low-temperature testing, is particularly important for EVs [37]. This kind of performance measurement should not only be carried out by vehicle manufactures like BYD; rather, governments should also participate in this, as the impact of climate on cars will ultimately result in additional carbon emissions and reduced environmental efficiency in each province. (3) The congestion coefficient mainly affects the environmental efficiency of ICEVs and HEVs with internal combustion engines as the power source. That is to say, with the increase in EV retention ratio in each province, the higher road congestion adaptability of EVs makes it unnecessary for the government to increase their investment in traffic congestion relief. However, this assumes that the energy consumption of EVs and ICEVs does not change significantly.

This study nevertheless has the following shortcomings: (1) there are still many non-localized data points in the GREET2021 database; (2) WTW's energy production and vehicle operation have a chronological sequence that needs to be reflected in either the data or the model; (3) in two-stage SBM-DEA, the priority of the second stage should also be considered.

Further research is needed to evaluate the carbon emissions and environmental efficiency of vehicles in different provinces. Can energy transportation bring about changes in carbon emissions and environmental efficiency in some provinces? Can power shortage caused by drought in the Yunnan-Guizhou Plateau in the second half of 2022 be quantified and simulated in the model? Can big data be further used to expand the coverage of cities and broaden the time range?

**Supplementary Materials:** The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su151511984/s1, Table S1. Temperature coefficients of provinces; Table S2. Congestion coefficient of provinces; Table S3. First-stage DEA data of provinces; Table S4. Second-stage DEA output of provinces; Table S5. First stage DEA regulation of pure electric model in provinces; Table S6. First stage DEA regulation of non-pure electric model in provinces; Table S7. Second stage DEA regulation of ICEVs in provinces; Table S8. Second stage DEA regulation of HEVs in provinces; Table S9. Second stage DEA regulation of PHEVs in provinces; Table S10. Second stage DEA regulation of EVs in provinces; Table S11. Efficiency changes of ICEVs TWW influenced by WTT; Table S12. Efficiency changes of HEVs TWW influenced by WTT; Table S13. Efficiency changes of PHEVs TWW influenced by WTT; Table S14. Efficiency changes of EVs TWW influenced by WTT.

**Author Contributions:** Conceptualization and original draft preparation, G.T.; writing—review and editing, M.Z. and F.B. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research is supported by the Scientific Research Plan Projects of Education Department of Shaanxi Provincial Government 22JK0099.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Data is available on request to the corresponding author.

**Data Availability Statement:** Not applicable.

**Acknowledgments:** The authors gratefully acknowledge the support of editors for your time and effort in reviewing and considering our manuscript for publication. The insightful comments and thoughtful feedback have greatly improved the quality of our work.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References


1. Onat, N.C.; Abdella, G.M.; Kucukvar, M.; Kutty, A.A.; Al-Nuaimi, M.; Kumbaroğlu, G.; Bulu, M. How eco-efficient are electric vehicles across Europe? A regionalized life cycle assessment-based eco-efficiency analysis. *Sustain. Dev.* **2021**, *29*, 941–956. [CrossRef]
2. Nimesh, V.; Kumari, R.; Soni, N.; Goswami, A.K.; Reddy, V.M. Implication viability assessment of electric vehicles for different regions: An approach of life cycle assessment considering exergy analysis and battery degradation. *Energy Convers. Manag.* **2021**, *237*, 114104. [CrossRef]
3. De Santis, M.; Silvestri, L.; Forcina, A. Promoting electric vehicle demand in Europe: Design of innovative electricity consumption simulator and subsidy strategies based on well-to-wheel analysis. *Energy Convers. Manag.* **2022**, *270*, 116279. [CrossRef]
4. Shafique, M.; Luo, X. Environmental life cycle assessment of battery electric vehicles from the current and future energy mix perspective. *J. Environ. Manag.* **2022**, *303*, 114050. [CrossRef]
5. Mamghaderi, M.; Mamkhezri, J.; Khezri, M. Assessing the environmental efficiency of OECD countries through the lens of ecological footprint indices. *J. Environ. Manag.* **2023**, *338*, 117796. [CrossRef]
6. Gan, Y.; Lu, Z.; He, X.; Wang, M.; Amer, A.A. Cradle-to-Grave Lifecycle Analysis of Greenhouse Gas Emissions of Light-Duty Passenger Vehicles in China: Towards a Carbon-Neutral Future. *Sustainability* **2023**, *15*, 2627. [CrossRef]
7. Pang, Q.; Qiu, M.; Zhang, L.; Chiu, Y.-H. Congestion effects of energy and capital in China's carbon emission reduction: Evidence from provincial levels. *Energy* **2023**, *274*, 127344. [CrossRef]
8. Wang, L.; Yu, Y.; Huang, K.; Zhang, Z.; Li, X. The inharmonious mechanism of $CO_2$, NOx, $SO_2$, and PM2.5 electric vehicle emission reductions in Northern China. *J. Environ. Manag.* **2020**, *274*, 111236. [CrossRef]
9. Zahoor, A.; Yu, Y.; Zhang, H.; Nihed, B.; Afrane, S.; Peng, S.; Sápi, A.; Lin, C.J.; Mao, G. Can the new energy vehicles (NEVs) and power battery industry help China to meet the carbon neutrality goal before 2060? *J. Environ. Manag.* **2023**, *336*, 117663. [CrossRef]
10. Gan, Y.; Lu, Z.; He, X.; Hao, C.; Wang, Y.; Cai, H.; Wang, M.; Elgowainy, A.; Przesmitzki, S.; Bouchard, J. Provincial Greenhouse Gas Emissions of Gasoline and Plug-in Electric Vehicles in China: Comparison from the Consumption-Based Electricity Perspective. *Environ. Sci. Technol.* **2021**, *55*, 6944–6956. [CrossRef]
11. Wu, D.; Guo, F.; Field, F.R.; De Kleine, R.; Kim, H.C.; Wallington, T.J.; Kirchain, R.E. Regional Heterogeneity in the Emissions Benefits of Electrified and Lightweighted Light-Duty Vehicles. *Environ. Sci. Technol.* **2019**, *53*, 10560–10570. [CrossRef] [PubMed]
12. Vukajlović, N.; Milićević, D.; Dumnić, B.; Popadić, B. Comparative analysis of the supercapacitor influence on lithium battery cycle life in electric vehicle energy storage. *J. Energy Storage* **2020**, *31*, 101603. [CrossRef]
13. Zhang, Z.; Sun, X.; Ding, N.; Yang, J. Life cycle environmental assessment of charging infrastructure for electric vehicles in China. *J. Clean. Prod.* **2019**, *227*, 932–941. [CrossRef]
14. Cristóbal, J.; Limleamthong, P.; Manfredi, S.; Guillén-Gosálbez, G. Methodology for combined use of data envelopment analysis and life cycle assessment applied to food waste management. *J. Clean. Prod.* **2016**, *135*, 158–168. [CrossRef]
15. Lozano, S.; Iribarren, D.; Moreira, M.T.; Feijoo, G. The link between operational efficiency and environmental impacts: A joint application of Life Cycle Assessment and Data Envelopment Analysis. *Sci. Total. Environ.* **2009**, *407*, 1744–1754. [CrossRef] [PubMed]
16. Zhang, X.; Xu, D. Assessing the eco-efficiency of complex forestry enterprises using LCA/time-series DEA methodology. *Ecol. Indic.* **2022**, *142*, 109166. [CrossRef]
17. Angulo-Meza, L.; González-Araya, M.; Iriarte, A.; Rebolledo-Leiva, R.; de Mello, J.C.S. A multiobjective DEA model to assess the eco-efficiency of agricultural practices within the CF+DEA method. *Comput. Electron. Agric.* **2019**, *161*, 151–161. [CrossRef]
18. Mirmozaffari, M.; Shadkam, E.; Khalili, S.M.; Yazdani, M. Developing a Novel Integrated Generalised Data Envelopment Analysis (DEA) to Evaluate Hospitals Providing Stroke Care Services. *Bioengineering* **2021**, *8*, 207. [CrossRef]
19. Chen, F.; Liu, J.; Liu, X.; Zhang, H. Static and Dynamic Evaluation of Financing Efficiency in Enterprises' Low-Carbon Supply Chain: PCA–DEA–Malmquist Model Method. *Sustainability* **2023**, *15*, 2510. [CrossRef]
20. Hsieh, J.-C.; Lu, C.-C.; Li, Y.; Chiu, Y.-H.; Xu, Y.-S. Environmental Assessment of European Union Countries. *Energies* **2019**, *12*, 295. [CrossRef]
21. Wang, Q.; Tang, J.; Choi, G. A two-stage eco-efficiency evaluation of China's industrial sectors: A dynamic network data envelopment analysis (DNDEA) approach. *Process. Saf. Environ. Prot.* **2021**, *148*, 879–892. [CrossRef]
22. Zhang, T.; Nakagawa, K.; Matsumoto, K. Evaluating solar photovoltaic power efficiency based on economic dimensions for 26 countries using a three-stage data envelopment analysis. *Appl. Energy* **2023**, *335*, 120714. [CrossRef]
23. Leu, J.-D.; Tsai, W.-H.; Fan, M.-N.; Chuang, S. Benchmarking Sustainable Manufacturing: A DEA-Based Method and Application. *Energies* **2020**, *13*, 5962. [CrossRef]
24. Álvarez-Rodríguez, C.; Martín-Gamboa, M.; Iribarren, D. Combined use of Data Envelopment Analysis and Life Cycle Assessment for operational and environmental benchmarking in the service sector: A case study of grocery stores. *Sci. Total. Environ.* **2019**, *667*, 799–808. [CrossRef]
25. Martín-Gamboa, M.; Iribarren, D.; García-Gusano, D.; Dufour, J. A review of life-cycle approaches coupled with data envelopment analysis within multi-criteria decision analysis for sustainability assessment of energy systems. *J. Clean. Prod.* **2017**, *150*, 164–174. [CrossRef]

26. Burchart-Korol, D.; Jursova, S.; Folęga, P.; Korol, J.; Pustejovska, P.; Blaut, A. Environmental life cycle assessment of electric vehicles in Poland and the Czech Republic. *J. Clean. Prod.* **2018**, *202*, 476–487. [CrossRef]
27. Wang, N.; Tang, G. A Review on Environmental Efficiency Evaluation of New Energy Vehicles Using Life Cycle Analysis. *Sustainability* **2022**, *14*, 3371. [CrossRef]
28. Wu, H.; Hu, Y.; Yu, Y.; Huang, K.; Wang, L. The environmental footprint of electric vehicle battery packs during the production and use phases with different functional units. *Int. J. Life Cycle Assess.* **2021**, *26*, 97–113. [CrossRef]
29. Shanmugam, K.; Gadhamshetty, V.; Yadav, P.; Athanassiadis, D.; Tysklind, M.; Upadhyayula, V.K.K. Advanced High-Strength Steel and Carbon Fiber Reinforced Polymer Composite Body in White for Passenger Cars: Environmental Performance and Sustainable Return on Investment under Different Propulsion Modes. *ACS Sustain. Chem. Eng.* **2019**, *7*, 4951–4963. [CrossRef]
30. Peters, J.F.; Baumann, M.; Zimmermann, B.; Braun, J.; Weil, M. The environmental impact of Li-Ion batteries and the role of key parameters—A review. *Renew. Sustain. Energy Rev.* **2017**, *67*, 491–506. [CrossRef]
31. Machedon-Pisu, M.; Borza, P.N. Are Personal Electric Vehicles Sustainable? A Hybrid E-Bike Case Study. *Sustainability* **2020**, *12*, 32. [CrossRef]
32. Hua, Y.; Liu, X.; Zhou, S.; Huang, Y.; Ling, H.; Yang, S. Toward Sustainable Reuse of Retired Lithium-ion Batteries from Electric Vehicles. *Resour. Conserv. Recycl.* **2021**, *168*, 105249. [CrossRef]
33. Wang, S.; Yu, J. A comparative life cycle assessment on lithium-ion battery: Case study on electric vehicle battery in China considering battery evolution. *Waste Manag. Res. J. Sustain. Circ. Econ.* **2021**, *39*, 156–164. [CrossRef] [PubMed]
34. Hendrickson, T.P.; Kavvada, O.; Shah, N.; Sathre, R.; Scown, C.D. Life-cycle implications and supply chain logistics of electric vehicle battery recycling in California. *Environ. Res. Lett.* **2015**, *10*, 014011. [CrossRef]
35. Schaubroeck, S.; Schaubroeck, T.; Baustert, P.; Gibon, T.; Benetto, E. When to replace a product to decrease environmental impact?—A consequential LCA framework and case study on car replacement. *Int. J. Life Cycle Assess.* **2020**, *25*, 1500–1521. [CrossRef]
36. Faria, R.; Marques, P.; Moura, P.; Freire, F.; Delgado, J.; de Almeida, A.T. Impact of the electricity mix and use profile in the life-cycle assessment of electric vehicles. *Renew. Sustain. Energy Rev.* **2013**, *24*, 271–287. [CrossRef]
37. Rupp, M.; Handschuh, N.; Rieke, C.; Kuperjans, I. Contribution of country-specific electricity mix and charging time to environmental impact of battery electric vehicles: A case study of electric buses in Germany. *Appl. Energy* **2019**, *237*, 618–634. [CrossRef]
38. Lee, D.-Y.; Elgowainy, A.; Kotz, A.; Vijayagopal, R.; Marcinkoski, J. Life-cycle implications of hydrogen fuel cell electric vehicle technology for medium- and heavy-duty trucks. *J. Power Sources* **2018**, *393*, 217–229. [CrossRef]
39. Liu, X.; Elgowainy, A.; Vijayagopal, R.; Wang, M. Well-to-Wheels Analysis of Zero-Emission Plug-In Battery Electric Vehicle Technology for Medium- and Heavy-Duty Trucks. *Environ. Sci. Technol.* **2021**, *55*, 538–546. [CrossRef]
40. Asamer, J.; Graser, A.; Heilmann, B.; Ruthmair, M. Sensitivity analysis for energy demand estimation of electric vehicles. *Transp. Res. Part D Transp. Environ.* **2016**, *46*, 182–199. [CrossRef]
41. Jradi, S.; Chameeva, T.B.; Delhomme, B.; Jaegler, A. Tracking carbon footprint in French vineyards: A DEA performance assessment. *J. Clean. Prod.* **2018**, *192*, 43–54. [CrossRef]
42. Pishgar-Komleh, S.H.; Żyłowski, T.; Rozakis, S.; Kozyra, J. Efficiency under different methods for incorporating undesirable outputs in an LCA+DEA framework: A case study of winter wheat production in Poland. *J. Environ. Manag.* **2020**, *260*, 110138. [CrossRef]
43. Rebolledo-Leiva, R.; Angulo-Meza, L.; Iriarte, A.; González-Araya, M.C.; Vásquez-Ibarra, L. Comparing two CF+DEA methods for assessing eco-efficiency from theoretical and practical points of view. *Sci. Total. Environ.* **2019**, *659*, 1266–1282. [CrossRef] [PubMed]
44. Vázquez-Rowe, I.; Iribarren, D.; Hospido, A.; Moreira, M.T.; Feijoo, G. Computation of Operational and Environmental Benchmarks Within Selected Galician Fishing Fleets. *J. Ind. Ecol.* **2011**, *15*, 776–795. [CrossRef]
45. Vásquez-Ibarra, L.; Rebolledo-Leiva, R.; Angulo-Meza, L.; González-Araya, M.C.; Iriarte, A. The joint use of life cycle assessment and data envelopment analysis methodologies for eco-efficiency assessment: A critical review, taxonomy and future research. *Sci. Total. Environ.* **2020**, *738*, 139538. [CrossRef]
46. Cortés, A.; Feijoo, G.; Fernández, M.; Moreira, M.T. Pursuing the route to eco-efficiency in dairy production: The case of Galician area. *J. Clean. Prod.* **2021**, *285*, 124861. [CrossRef]
47. Turner, I.; Heidari, D.; Pelletier, N. Environmental impact mitigation potential of increased resource use efficiency in industrial egg production systems. *J. Clean. Prod.* **2022**, *354*, 131743. [CrossRef]
48. Torregrossa, D.; Marvuglia, A.; Leopold, U. A novel methodology based on LCA+DEA to detect eco-efficiency shifts in wastewater treatment plants. *Ecol. Indic.* **2018**, *94*, 7–15. [CrossRef]
49. Song, A.; Huang, W.; Yang, X.; Tian, Y.; Juan, Y.; Xing, Q. Two-Stage Cooperative/Non-Cooperative Game DEA Model with Decision Preference: A Case of Chinese Industrial System. *Big Data Res.* **2022**, *28*, 100303. [CrossRef]
50. Jin, X.; Zou, B.; Wang, C.; Rao, K.; Tang, X. Carbon Emission Allocation in a Chinese Province-Level Region Based on Two-Stage Network Structures. *Sustainability* **2019**, *11*, 1369. [CrossRef]

51. Campitelli, A.; Schebek, L. How is the performance of waste management systems assessed globally? A systematic review. *J. Clean. Prod.* **2020**, *272*, 122986. [CrossRef]
52. Liu, Y.; Qiao, J.; Xu, H.; Liu, J.; Chen, Y. Optimal Vehicle Size and Driving Condition for Extended-Range Electric Vehicles in China: A Life Cycle Perspective. *PLoS ONE* **2020**, *15*, e0241967. [CrossRef] [PubMed]
53. Qiao, Q.; Zhao, F.; Liu, Z.; Hao, H.; He, X.; Przesmitzki, S.V.; Amer, A.A. Life Cycle Cost and GHG Emission Benefits of Electric Vehicles in China. *Transp. Res. Part D Transp. Environ.* **2020**, *86*, 102418. [CrossRef]
54. Ren, L.; Zhou, S.; Ou, X. Life-Cycle Energy Consumption and Greenhouse-Gas Emissions of Hydrogen Supply Chains for Fuel-Cell Vehicles in China. *Energy* **2020**, *209*, 118482. [CrossRef]
55. Wang, Y.; Zhou, G.; Li, T.; Wei, X. Comprehensive Evaluation of the Sustainable Development of Battery Electric Vehicles in China. *Sustainability* **2019**, *11*, 5635. [CrossRef]
56. Zeng, D.; Dong, Y.; Cao, H.; Li, Y.; Wang, J.; Li, Z.; Hauschild, M.Z. Are the electric vehicles more sustainable than the conventional ones? Influences of the assumptions and modeling approaches in the case of typical cars in China. *Resour. Conserv. Recycl.* **2021**, *167*, 105210. [CrossRef]
57. MHWS. ReCiPe 2016 v1.1. The Netherlands: National Institute of Public Health and the Environment. 2017. Available online: https://www.rivm.nl/en/life-cycle-assessment-lca/downloads (accessed on 5 May 2022).
58. Masnadi, M.S.; El-Houjeiri, H.M.; Schunack, D.; Li, Y.; Roberts, S.O.; Przesmitzki, S.; Brandt, A.R.; Wang, M. Well-to-refinery emissions and net-energy analysis of China's crude-oil supply. *Nat. Energy* **2018**, *3*, 220–226. [CrossRef]
59. NBS. *China Energy Statistical Yearbook 2021*; China Statistics Press: Beijing, China, 2021; Available online: http://cnki.nbsti.net/CSYDMirror/area/yearbook/Single/N2021050066?z=D26 (accessed on 2 August 2022).
60. International Energy Agency (IEA). *World Energy Statistics and Balance 2019*; International Energy Agency: Paris, France, 2019; Available online: https://www.iea.org/data-and-statistics/data-product/world-energy-statistics-and-balances (accessed on 5 May 2022).
61. CEC. *2019 Statistical Compilation of the Electric Power Industry*; China Statistics Press: Beijing, China, 2019. Available online: http://www.nea.gov.cn/ (accessed on 11 August 2022).
62. NBS. *2019 China Electric Power Yearbook*; China Electric Power Press: Beijing, China, 2019; Available online: https://ds.cnki.net/KNavi/yearbook/Detail/NUYY/YZGDL?NaviID=&NO= (accessed on 1 July 2021).
63. Shen, W.; Han, W.; Wallington, T.J. Current and Future Greenhouse Gas Emissions Associated with Electricity Generation in China: Implications for Electric Vehicles. *Environ. Sci. Technol.* **2014**, *48*, 7069–7075. [CrossRef]
64. Qu, S.; Liang, S.; Xu, M. $CO_2$ Emissions Embodied in Interprovincial Electricity Transmissions in China. *Environ. Sci. Technol.* **2017**, *51*, 10893–10902. [CrossRef]
65. MacLean, H.L.; Lave, L.B. Evaluating automobile fuel/propulsion system technologies. *Prog. Energy Combust. Sci.* **2003**, *29*, 1–69. [CrossRef]
66. de Souza, L.L.; Lora, E.E.S.; Palacio, J.C.E.; Rocha, M.H.; Renó, M.L.G.; Venturini, O.J. Comparative environmental life cycle assessment of conventional vehicles with different fuel options, plug-in hybrid and electric vehicles for a sustainable transportation system in Brazil. *J. Clean. Prod.* **2018**, *203*, 444–468. [CrossRef]
67. Nordelöf, A.; Messagie, M.; Tillman, A.-M.; Söderman, M.L.; Van Mierlo, J. Environmental impacts of hybrid, plug-in hybrid, and battery electric vehicles—What can we learn from life cycle assessment? *Int. J. Life Cycle Assess.* **2014**, *19*, 1866–1890. [CrossRef]
68. Marmiroli, B.; Venditti, M.; Dotelli, G.; Spessa, E. The transport of goods in the urban environment: A comparative life cycle assessment of electric, compressed natural gas and diesel light-duty vehicles. *Appl. Energy* **2020**, *260*, 114236. [CrossRef]
69. Paudel, A.M.; Kreutzmann, P. Design and performance analysis of a hybrid solar tricycle for a sustainable local commute. *Renew. Sustain. Energy Rev.* **2015**, *41*, 473–482. [CrossRef]
70. Ruan, J.; Walker, P.D.; Watterson, P.A.; Zhang, N. The dynamic performance and economic benefit of a blended braking system in a multi-speed battery electric vehicle. *Appl. Energy* **2016**, *183*, 1240–1258. [CrossRef]
71. Cai, L.; Lv, W.; Xiao, L.; Xu, Z. Total carbon emissions minimization in connected and automated vehicle routing problem with speed variables. *Expert Syst. Appl.* **2021**, *165*, 113910. [CrossRef]
72. Desreveaux, A.; Bouscayrol, A.; Trigui, R.; Hittinger, E.; Castex, E.; Sirbu, G. Accurate energy consumption for comparison of climate change impact of thermal and electric vehicles. *Energy* **2023**, *268*, 126637. [CrossRef]
73. Kamath, D.; Arsenault, R.; Kim, H.C.; Anctil, A. Economic and Environmental Feasibility of Second-Life Lithium-Ion Batteries as Fast-Charging Energy Storage. *Environ. Sci. Technol.* **2020**, *54*, 6878–6887. [CrossRef]
74. Wang, W.; Bengler, K.; Jiang, X. *Green Intelligent Transportation Systems*; Springer: Singapore, 2019.
75. Chen, Y.; Cook, W.D.; Li, N.; Zhu, J. Additive efficiency decomposition in two-stage DEA. *Eur. J. Oper. Res.* **2009**, *196*, 1170–1176. [CrossRef]
76. Kao, C.; Hwang, S.-N. Efficiency decomposition in two-stage data envelopment analysis: An application to non-life insurance companies in Taiwan. *Eur. J. Oper. Res.* **2008**, *185*, 418–429. [CrossRef]
77. Li, Y.; Chen, Y.; Liang, L.; Xie, J. DEA models for extended two-stage network structures. *Omega* **2012**, *40*, 611–618. [CrossRef]

78. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [CrossRef]
79. Garcia, R.; Freire, F.; Clift, R. Effects on Greenhouse Gas Emissions of Introducing Electric Vehicles into an Electricity System with Large Storage Capacity. *J. Ind. Ecol.* **2018**, *22*, 288–299. [CrossRef]