Energy 335 (2025) 137823

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Environmental emission analysis of frugal electric vehicles from a life cycle perspective: A case study

Dingsong Cui [a], Haibo Chen [a,*], David Watling [a], Ye Liu [a], Jin Liu [a], Chenxi Wang [a], Mengyuan Xu [a], Shuo Wang [b,**], Zhenpo Wang [b,c], Chengcheng Xu [d]

[a] Institute for Transport Studies, University of Leeds, Leeds, LS2 9JT, UK
[b] Collaborative Innovation Centre for Electric Vehicles and National Engineering Research Centre for Electric Vehicles, Beijing Institute of Technology, Beijing, 100081, China
[c] Beijing Institute of Technology Chongqing Innovation Centre, Chongqing, 401120, China
[d] School of Transportation, Southeast University, Nanjing, 211189, China

ARTICLE INFO

Handling editor: X Ou

Keywords:
Frugal electric vehicles
Life cycle assessment
Usage patterns
Electricity mix
Environmental benefits

ABSTRACT

Frugal electric vehicles (EV) are designed for lower energy consumption with lower battery capacity, but their life-cycle emissions have been overlooked in previous studies. Herein, this paper collects 2.38 million light-duty EV operational data to analyse usage patterns based on energy consumption, daily mileage and annual utilisation. By integrating 12 recognised usage patterns with 6 electricity mixes, the study assesses the emission reduction potential and trade-off period of frugal EVs compared to counterpart internal combustion engine vehicles (ICEVs). The results show that about 70 % of frugal EV users would like to take a short daily travel with high utilisation rate and low energy consumption. From macro perspectives, CO_2 and VOC emissions reductions are significant, while NO_x, SO_x, and PM are not achieved significant reductions. In terms of micro usage patterns, low-utilisation and low-daily travel result in less emission reduction opportunities. In general, about 79 % of frugal EVs can achieve the CO_2 emission reduction compared to frugal ICEVs based on 12-year longevity simulation. 30 % and 30.3 % of frugal EVs can achieve $PM_{2.5}$ and NO_x emissions reductions in high clean electricity regions. In summary, this study provides insights for policymakers and manufacturers aiming to enhance the sustainability of frugal EVs.

Abbreviations

All-electric driving range	AER	Low-speed electric vehicle	LSEV
Confidence interval	CI	Light-duty passenger vehicle	LDPV
Electric vehicle	EV	Middle-Clean energy	Midd-Clea
Functional unit	FU	Recency, Monetary, and Frequency	RMF
Greenhouse gas	GHG	Sport utility vehicle	SUV
Gaussian mixed model	GMM	Traditional energy	Tra
High-Clean energy	High-Clea	Utilisation' rate	UR
Internal combustion engine vehicle	ICEV	Vehicle kilometre travelled	VKT
Life cycle assessment	LCA	Well-to-Wheel	WtW
Light-duty electric vehicle	LDEV		

1. Introduction

It has been widely accepted that transportation electrification is an ever-growing approach to improving environmental sustainability and reducing greenhouse gas (GHG) emissions [1,2]. According to the International Energy Agency, achieving net-zero emissions by 2050 will require significant growth in electric vehicle (EV) adoption, with the global stock of EVs projected to exceed 30 million by 2030 [3]. While large-scale EV deployment significantly reduces tailpipe emissions, it also shifts some of environmental burdens from the road to electricity grid and production of battery materials. When considering the emissions throughout the life cycle of an EV, there are still some voices of

* Corresponding author. Institute for Transport Studies, University of Leeds, Leeds, LS2 9JT, UK.
** Corresponding author. Beijing Institute of Technology, Zhongguancunnan street 5, 100081, Beijing, China.
E-mail addresses: h.chen@leeds.ac (H. Chen), Shuo.Wang@bit.edu.cn (S. Wang).

https://doi.org/10.1016/j.energy.2025.137823
Received 5 February 2025; Received in revised form 10 July 2025; Accepted 29 July 2025
Available online 30 July 2025

scepticism [4–6]; however, the wide majority of studies and review studies state a remarkable advantage in terms of GHG emissions [7–9].

There is a noticeable trend towards developing longer all-electric driving range (AER) for EVs, which are typically paired with medium- or large-sized vehicles. However, some studies emphasised that ultra-long-AER EVs cannot really solve range anxiety of consumers except by reducing charging frequency, even resulting in higher total owner costs and more battery production emissions [10,11]. For personal light-duty electric vehicles (LDEVs), most users drive them as commuting vehicles, representing a shorter travel demand in a day. Based on the statistical results from Annual Report on New Energy Vehicle Industry in China (https://www.ndanev.com/), the average daily vehicle kilometre travelled (VKT) of all kinds of personal EVs is about 40 km in 2024, while the average of AER is nearly 500 km. Therefore, compared to a smaller and appropriately sized battery, a vehicle with a larger battery capacity and lower usage intensity takes longer to offset the carbon emissions and environmental impact of battery production through emissions reductions during the driving phase. Frugal EVs, with a small-sized battery (preferably swappable), lightweight cabin and lower energy consumption, is designed for this purpose. The definition of the frugal EV is a compact two-seater vehicle designed for everyday urban use (https://zev-up.eu/). There have been 10 typical frugal EV model collected to illustrate the AER and battery capacity in Fig. 1a–b, respectively. In China, this kind of EV is classified as a part of A00-segment, with a wheelbase of less than 2300 mm. For other regions, such as Europe, frugal EV is classified into heavy quadricycles with a maximum mass less than 450 kg excluding driver and battery (called L7e category in European Union vehicle classification), while in Japan, it can be defined as a micro-mobility (scheme) with a dimension of $3.4 \times 1.18 \times 2.0$ m. Nevertheless, the vehicle classification standard is based on Chinese market, because the electricity structure used in this paper is based on China. As shown in Fig. 1c, the proportion of A00-segment EVs is about 49 % of the passenger LDEV market in 2022 in China (excluding sport utility vehicles, SUVs). However, since there are no specific labels for frugal EVs in China EV market, according to the average AER (about 120 km) and battery capacity (about 10 kWh) collected above and two of passenger capacity, the proportion of frugal EVs is about 27 % of all A00-segment LDEVs. Since the adjustment of EV subsidy policies in 2018, the assessment criteria have shifted from a single focus on AER to a comprehensive evaluation of range, battery energy density, and vehicle energy consumption. As a result, models with a range of less than 150 km are no longer eligible for subsidies, which has had a negative impact on frugal EV development However, six government departments in China issued the ‘Notice on Strengthening the Management of Low-Speed Electric Vehicles (LSEV),’ requiring local authorities to regulate and rectify LSEVs, strictly prohibiting the expansion of production capacity, and accelerating efforts to standardise management, further limiting the expansion and sales of such vehicles. Given these limitations, frugal EVs present a viable alternative. Currently, the nationwide LSEV fleet exceeds 6 million, primarily concentrated in third- and fourth-tier cities and rural areas. Additionally, in the 2024 EV Rural Promotion Campaign launched by five government ministries and agencies in China, 27 out of the 99 promoted models are classified as A00-segment EVs, providing greater market potential and application scenarios for this vehicle category.

There have been many studies focusing on the life cycle assessment (LCA) of LDEVs. However, most LCA studies have focused on medium- or large-sized LDPVs and have ignored the benefit assessment of frugal EVs. For instance, Qiao et al. [12] analysed the life cycle cost and GHG emissions of an A-segment LDEV with a 27-kWh battery capacity compared to a similar internal combustion engine vehicle (ICEV). It was assumed that both vehicles could drive 200,000 km in 12 years of age. The driving cycle in Beijing and the standard cycle (New European Driving Cycle) were both used to calculate energy consumption. The

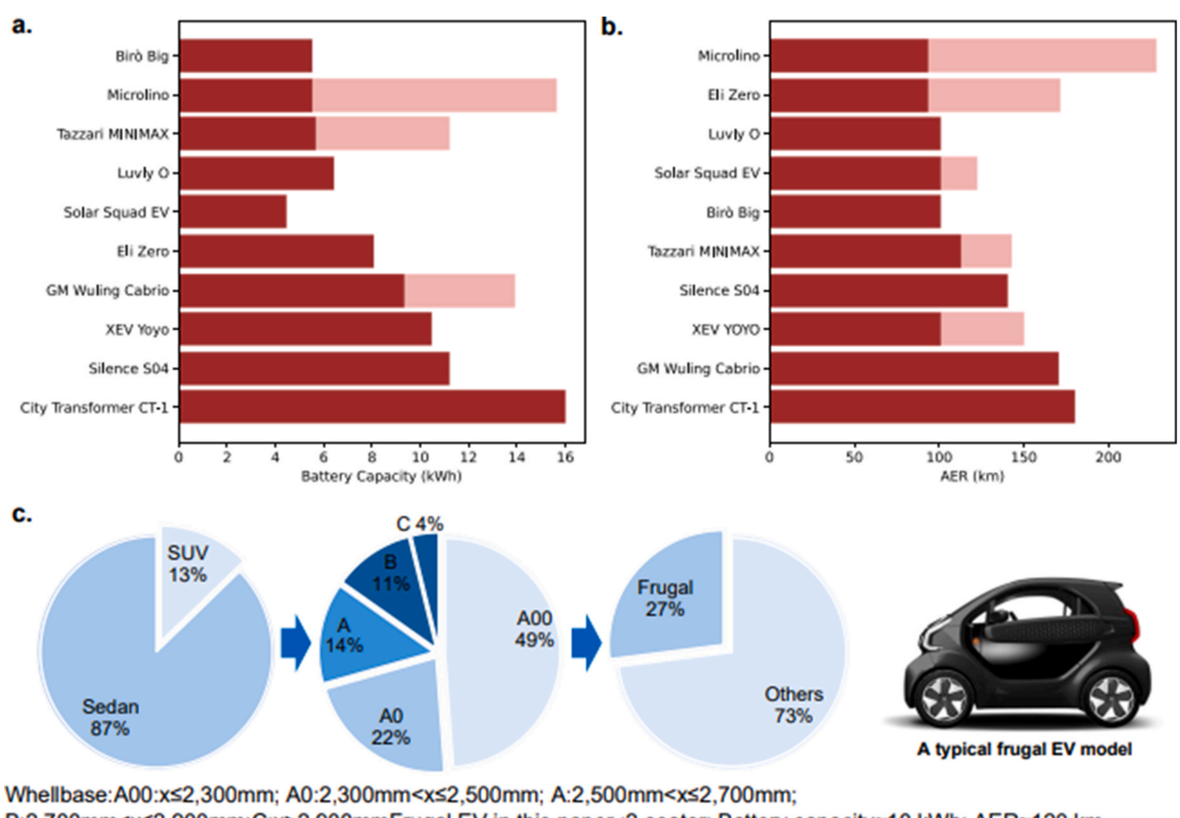

Fig. 1. The definitions and information of frugal EVs. **a** Battery capacity and **b** AER of ten typical frugal EV model **c** Proportion for different levels in the market of LDPVs in China in 2022.

results showed that the life-cycle GHG emissions of an EV are about 29 % lower than those of an ICEV. If the lifetime mileage is not as long as expected, the gap of GHG emissions would be smaller. Wu et al. [13] calculated and compared the life cycle GHG emissions from EVs and ICEVs in different electricity mix scenarios in 2010, 2014 and 2020. The life-cycle VKT of vehicles was assumed as 150,000 km. The study highlighted the importance of the decarbonisation of the electricity system. Huang et al. [14] focused on the L-category LDPV electrification and compared with the e-bike usage and ICEV usage. The life cycle VKT of ICEVs and BEVs were assumed as 273,588 km and 193,121 km, respectively. That can be in the line with the rule of 'Lower usage intensity for an EV than an ICEV' proposed in several previous studies [14–16]. Results showed that EVs reduce GHGs significantly, and other lifecycle emissions from EVs are close to, or even higher than, ICEVs although the exposure risks are different. Wei et al. [17] analysed top 10 sold EVs (including 7 plug-in hybrid electric vehicles, PHEVs, 2 BEVs and 1 extended range EV) in Shanghai and assessed the environmental and economic benefits of different EVs with different energy mixes. The study primarily focused on the analysis of medium-sized LDPVs with a 150,000 km life-cycle VKT and 15 years of age. The electricity transfer from other locations was considered comprehensively in this paper. In conclusion, usage patterns of these EVs were often directly assumed from the usage of ICEVs. For a more larger scale electricity transfer, Li et al. [18] proposed a quasi-input-output model to assess the emission transfer between different provinces when using EVs. This paper extracted 8 kinds of EVs including A-segment, B-segment and above cars, A0-segment, A-segment SUVs, and multi-purpose vehicles. The annual VKT of each province has been collected to assess the LDPV electrification benefits. The article clearly explained the advantages of using macro-level statistical features of EVs to evaluate the benefits of LDPV electrification. Although some studies have used real-world operating data, the use of such macro-statistics (e.g., in a province or a region) in evaluating vehicle electrification may introduce aggregate-level errors due to variations in travel demand and usage patterns among EV users [19,20]. In terms of previous small sized EV-related studies, Faria et al. [21] provided a detailed analysis of compact and sub-compact EVs with different kinds of electricity mixes. The annual distance was assumed as 20,000 km. This is one of few articles that analyses frugal EVs, especially in the early stage of vehicle electrification. Pierpaolo et al. [22] compared the environmental performances of EVs and homologous gasoline and diesel vehicles focusing on some small-sized vehicle models, such as Smart Fortwo, Chevrolet Spark, Fiat 500, etc. The analysis showed that EVs outperform traditional ones in terms of GHGs, non-renewable resource depletion, and urban air pollutant emissions. However, they were less competitive in life cycle impact categories such as water eutrophication and human toxicity, mainly due to the environmental burden of the battery life cycle. Helmers et al. [23] analysed one Smart vehicle model (a typical mini car) which was converted from combustion to electric in a laboratory project. The vehicle operated as an ICEV until it reached 100,000 km, after which it was retrofitted and converted into an EV. The results showed that the electric conversion of a used ICEV can save an additional 16 % CO_2 of the environmental impact over a lifetime. Zhang et al. [24] collected three models of EVs, including A00, A0 and A segments, and analysed the energy consumption of the life cycle oriented to the car-sharing market. Although 3000 EV operational data were used in this paper, the research topic only focused on the energy efficiency rather than emissions. Nevertheless, there remains a research gap in conducting a comprehensive and large-scale LCA of frugal vehicle electrification.

From the perspective of the fuel cycle, it should be noted that cleaner energy resources have been applied to reduce emissions from power plants. Advanced emission reduction technologies were also developed to replace high-emission power generation technologies [25]. The electricity is becoming cleaner. This makes it possible to make contributions to reduce emissions for the life cycle. However, considering other participants in the fuel cycle, usage intensity is another important factor in determining the emission reduction [26]. Based on the focus of the group of frugal EVs in this paper, the usage patterns of them are still unclear, which has a strong relationship with emissions reductions. Therefore, we should pay more attention to the emissions reduction opportunities of different frugal EV users [27]. All above, there are two questions are followed in this paper.

(1) What usage patterns exist for LDEVs in real-world conditions, and which category do frugal EVs fall into?
(2) What opportunities of frugal EVs can achieve emission reduction under different usage patterns with different usage intensity?

To address these questions, this paper collects over 2.38 million LDEV operational data in 2022 from the OpenLab of the National Big Data Alliance of New Energy Vehicles. This paper aims to provide a comprehensive evaluation on environmental emissions of frugal EVs in China. The study not only considers the basic framework of the traditional LCA model but also focuses more on the usage patterns that have not been concerned specifically in previous studies. Although the LCA framework is well-established, previous studies have not addressed large-scale real-world EV operational data with detailed usage patterns across different EV users, rather than relying on a single assumed sample. The main contributions of this paper include the following aspects.

(1) The paper proposes an EV usage pattern recognition method based on the Gaussian mixed model (GMM). Considering the necessary elements in LCA model, energy consumption, daily VKT and annual utilisation rate (UR) are used to establish this cluster model based on the concept of the Recency, Monetary, and Frequency (RMF) framework. Different from prior usage pattern cluster models, this model is oriented to the LCA of EVs. There are 12 usage patterns extracted from the cluster model based on a real-world dataset with 2.38 million LDEVs, representing different usage intensities. The data analysis helps us to understand how people use frugal EVs in real-world situation, which can guide automakers accurately identify the target groups for their products.
(2) To answer the question of the life-cycle benefits of frugal EVs, the paper establishes an LCA model based on comprehensive micro-usage patterns from GMM model and detailed electricity patterns. To our knowledge, no studies have combined detailed usage patterns (more than 90,000 frugal EV used in this paper) with LCA. Most studies only use macro-statistics of usage patterns as input. The electricity transfers in each region are considered in the model. The quantitative results of CO_2, VOC, NO_x, SO_x, $PM_{2.5}$, and PM_{10} emissions of each phase (such as battery production and vehicle production) in the LCA are provided to assess the environmental emissions of frugal vehicle electrification. Meanwhile, 95 % confidence interval (CI) is used to describe the range of the statistical value, because the results are calculated based on each frugal EV from different usage patterns. Additionally, the period of the emission balance is also assessed to determine how many years are needed for a frugal EV to achieve emission reduction benefits compared with a frugal ICEV with different usage patterns in different electricity patterns. Using our unique dataset, we also calculate the proportion of frugal EVs that have the potential for emission reductions across different conditions.

The remainder of the paper is structured as follows: Section 2 provides the methodology of the LCA model including goal and scope, functional unit and system boundary. Section 3 introduces the life cycle inventory analysis, covering vehicle production phase, electricity production phase, vehicle use phase and disposal phase. Section 4 presents the emission reduction opportunities of frugal EVs in six provinces with different electricity mix structures from the perspective of macro- and micro usage patterns. The trade-off period and reduction proportion of replacing a frugal ICEV with a frugal EV is assessed, while the policy implications and future considerations of this paper are discussed in this section. Finally, section 5 summarises the results of this paper. The rest of the necessary materials are provided in the **Appendix** and the **Supplementary**.

2. Methodology

2.1. Goal and scope definition

The goal of this study is to quantify the proportion of frugal EVs with the potential to reduce emissions and assess their environmental benefits from a Cradle-to-Grave perspective. This model compares the environmental impacts, including CO_2, NO_x, SO_x, VOC, $PM_{2.5}$ and PM_{10}, of frugal personal EVs and frugal ICEVs operating across six provinces with different electricity mixes in 2021. Unlike traditional LCA studies that rely on macro-level assumptions or very limited sample sizes, this assessment incorporates large-scale real-world operation EV data. By emphasising the heterogeneity of usage patterns rather than assuming a fixed lifetime mileage or constant energy consumption, our approach provides a more elaborate and realistic evaluation of environmental impacts.

2.2. Functional unit

The functional unit (FU) is a critical component of an LCA as it ensures the comparability of results. Unlike previous studies that assume a constant lifetime mileage, this study accounts for large-scale real-world frugal EV operations, leading to varying lifetime mileages across different EV users. To maintain consistency in comparison, the FU in this research is defined as 1 km of vehicle travel.

2.3. System boundary

The basic structure of LCA for EVs is shown in Fig. 2 a. The assessment can be divided into fuel cycle and vehicle cycle. In terms of fuel cycle (i.e., well-to-wheel, WtW), it should be noted that the electricity structure is important for emissions of the well-to-tank phase, while the life cycle VKT and energy consumption of the vehicle is crucial for the emissions of the tank-to-wheel phase. In terms of the vehicle cycle, previous studies have illustrated that the emissions during the vehicle production are slightly higher than that of ICEVs, mainly due to energy and materials consumption in EV batteries production [28,29]. Therefore, it is necessary to clarify the boundaries of the system.

The research boundary consists of life cycle of the vehicles, which includes the vehicle production phase, electricity production phase, vehicle use phase and disposal phase, as shown in Fig. 2b. Within the system boundary, vehicle production includes five elements: batteries, fluids, other components, assembly, disposal and recycling. It covers the acquisition of raw materials, manufacturing and distribution of parts, vehicle assembly and end-of-life disposal. Each element includes its own supply chain and replacements (e.g. tyres, batteries). Moreover, the vehicle disposal is classified in this phase, as it is not the focus of our comparison while the battery disposal is the main difference between these two kinds of vehicles and. Due to the power resources of electricity

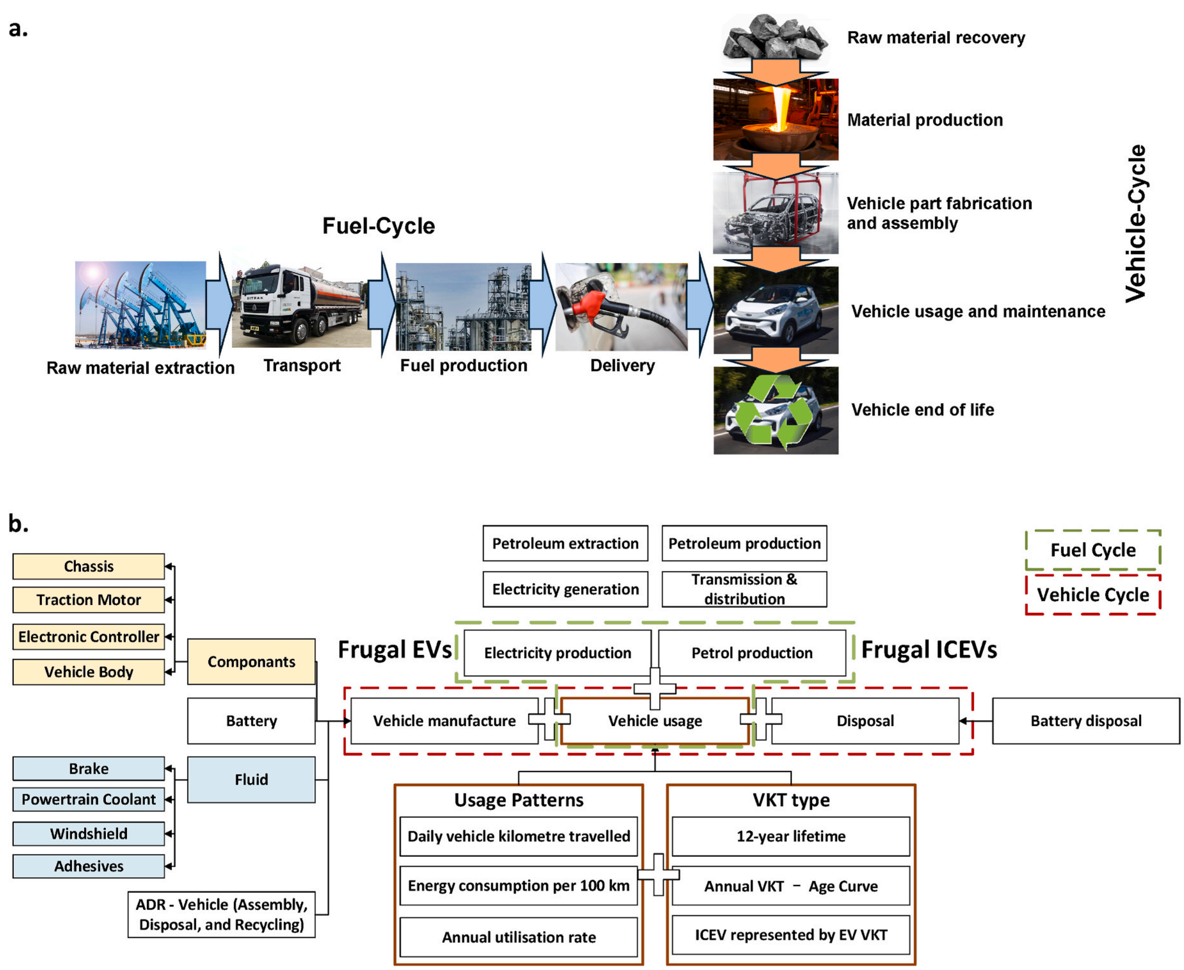

Fig. 2. Fundamental information for **a** LCA model and **b** boundaries of system.

and fuel, the structure of EVs and ICEVs has some differences, such as the boundaries of fuel vehicles are concentrated in engine and transmission manufacturing, while the system boundaries of EVs need to cover the entire life cycle of power batteries. However, since this study focuses primarily on the usage phase, it is assumed that the frugal EV is an ICEV-to-EV conversion vehicle, meaning that the vehicle body, chassis, and tyres remain nearly identical. The difference is battery, electric motor, controller, transmission. Although the vehicle body of a frugal EV may be slightly lighter than that of a frugal ICEV due to lightweighting trends, the chassis may be slightly heavier due to battery pack installation. However, these minor differences are not considered in this study.

During the fuel cycle, ICEV and EV are run using petrol and electricity, respectively. In terms of the electricity production, it includes the electricity mix for charging, the various fossil fuel and renewable energy sources used for electricity generation in each selected province. The spatial system boundary covers the electricity mix of six representative provinces, each with a distinct energy structure and energy transfer pattern in 2021. In addition, we use the petrol that includes 10 % ethanol (E10) because the supply of E10 is expected to cover all the regions across the country [30]. The emission of petroleum extraction and production, electricity generation, transmission & distribution are all integrated into the emission factors during the vehicle's operation. About the vehicle use phase, it is assumed that the total vehicle lifespan is 12 years, while the lifetime mileage of frugal EVs and ICEVs is the same. Vehicle maintenance and repair is scaled to a fraction of the production in the literature [14], which is excluded from this study. Finally, the battery disposal is considered in the disposal phase.

3. Life cycle inventory analysis

3.1. Vehicle croduction phase

The EV operational data are sourced from the OpenLab of the National Big Data Alliance of New Energy Vehicles (http://www.ndanev.com/), established in China in 2016. The data covers all the cities in China where EV are currently in operation. The total number of EVs used in this study has exceeded 2.38 million. After pre-processing and data extraction based on the frugal EV selection rules in the Introduction, more than 90,000 frugal EVs operating in six typical provinces are selected for analysis in this paper. The average AER is around 120 km; the average battery capacity is about 9.3 kWh, while the average curb weight of the frugal EV is about 620 kg. The mass of a frugal ICEV is about 580 kg, which is a little lighter than that of frugal EVs with a power battery. Although EV has fewer components, the large battery pack required for electric propulsion significantly adds to the overall vehicle weight [13,31]. The power battery mass of Li-ion material is set at 62 kg with an energy density of 150 Wh/kg. This battery energy density is at a moderate level among LDEV power batteries. The compositional data of the vehicle components and the battery material in the vehicle cycle were obtained from the GREET 2023 (Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation) model (http://greet.es.anl.gov/). The emission factors of each material used in vehicle manufacturing and the energy consumption of parts machining and vehicle assembly are collected from Ref. [30] See the **Supplementary** for specific parameters and data resources.

3.2. Electricity production phase

Electricity resource is a crucial factor in the LCA of EVs and differs significantly from ICEVs in terms of emissions [32]. Electricity generation resources for each province are gathered, covering both traditional energy sources (e.g., coal, gas) and clean energy sources (e.g., nuclear, wind power, biomass, hydropower). The electricity structure data are sourced from the China Electric Power Statistical Yearbook in 2021 (https://www.stats.gov.cn/zs/tjwh/tjkw/tjzl/202302/t20230215_1907998.html), which is an authoritative annual publication that comprehensively reflects statistical data on China's power industry, including electricity production, consumption, supply and demand, and investment. The yearbook provides detailed information on the basic status of power enterprises, electricity generation, power consumption structure, energy mix, power sector investment, as well as inter-provincial electricity transmission. This dataset has been used as a publicly available data sources for models to study renewables integration in China's power system [33,34]. Emission factors of each energy resources are collected based on the previous studies [30,35]. See **Supplementary** for the proportion of the energy resources in each area and the emission factors used in this paper.

In addition, the inter-provincial electricity transmission is considered in this paper, which means the emission factor of electricity generation not only considers the location electricity structure, but also calculates the electricity obtained from other regions. In this paper, we refer to the CO_2 emission factor calculation method proposed by Ministry of Ecology and Environment of the China in 2021 (https://www.mee.gov.cn/xxgk2018/xxgk/xxgk01/202404/t20240412_1070565.html). Here, we use CO_2 as an example to describe the calculation method of emission factors. The calculation method is provided in equation (1).

$$EF_p = \frac{Em_p + \sum_n (EF_n \times E_{imp,n,p}) + \sum_k (EF_k \times E_{imp,k,p}) + (EF_r \times E_{imp,r,p})}{E_p + \sum_n E_{imp,n,p} + \sum_k E_{imp,k,p} + E_{imp,r,p}} \tag{1}$$

where EF_p is the emission factor (e.g., CO_2, NO_x) in pth province, kg/kWh; Em_p is the emission from the local electricity generation, kg; EF_n is the emission factor of the nth province importing electricity to the pth province, kg/kWh; $E_{imp,n,p}$ is the transfer electricity from nth province to pth province, kWh; EF_k is the emission factor from kth country, kg/kWh; $E_{imp,k,p}$ is the transfer electricity from kth country to pth province, kWh; EF_r is the emission factor of the local regional power grid, kg/kWh; $E_{imp,r,p}$ is the transfer electricity from rth region to pth province, kWh; E_p is the electricity generation in pth province, kWh; r is the power grid region where province p is located.

According to the local electricity generation structure, it can be divided into three kinds: Traditional energy (Tra), Middle-Clea energy (Midd-Clea) and High-Clea energy (High-Clea). The proportion of clean energy is between 30 % and 50 % for Midd-Clea, while that of High-Clea is more than 50 %. Besides, the local energy will be defined as Tra, representing the main electricity generated by coal-fired power. Then, consider the electricity transfer from other locations, there are three kinds including Import (Local generation proportion <95 %), Self (95 % ≤ Local generation proportion ≤105 %) and Export (Local generation proportion >105 %). The local generation proportion calculation is shown in equation (2).

$$LocalGenerationProportion = Local/(Import + Local - Export) \times 100\,\% \tag{2}$$

Finally, the typical electricity generation are extracted in six patterns, which are provided in Table 1, and the specific parameters are shown in Table 2. These electricity generation patterns represent the typical scenarios of provinces in China with a high deployment of frugal EVs. The following analysis is all based on these electricity generation patterns. See **Supplementary** for specific parameters.

3.3. Vehicle use phase

Unlike previous studies, this paper places a stronger emphasis on understanding the real-world usage behaviour of EVs. While simulations typically assume that EVs are used under ideal conditions, in practice, users tend to follow their own travel preferences. Energy consumption and life cycle VKT are critical indicators for assessing the emission reduction potential of EVs. Therefore, this section provides a method for

Table 1
Electricity generation pattern definitions.

Patterns	Definitions
Tra-Export	The local electricity generation structure primarily consists of traditional energy sources; The exported electricity is much greater than the imported electricity.
Tra-Import	The local electricity generation structure primarily consists of traditional energy sources; The imported electricity is much greater than the exported electricity.
Midd-Clea-Export	The proportion of clean energy in the local electricity mix is between 30 % and 50 %; The exported electricity is much greater than the imported electricity.
Midd-Clea-Self	The proportion of clean energy in the local electricity mix is between 30 % and 50 %; The imported electricity is nearly equal to the exported electricity.
Midd-Clea-Import	The proportion of clean energy in the local electricity mix is between 30 % and 50 %; The imported electricity is much greater than the exported electricity.
High-Clea-Export	The proportion of clean energy in the local electricity mix is More than 50 %; The exported electricity is much greater than the imported electricity.

Table 2
Energy structure of each electricity generation pattern.

Patterns	Traditional energy	Clean energy	Local generation proportion
Tra-Export	87.26 %	12.74 %	110.88 %
Tra-Import	79.20 %	20.80 %	82.50 %
Midd-Clea-Export	57.15 %	42.85 %	106.27 %
Midd-Clea-Self	55.25 %	44.75 %	97.51 %
Midd-Clea-Import	57.43 %	42.57 %	81.83 %
High-Clea-Export	14.30 %	85.70 %	130.62 %

establishing LDEV usage pattern. There is also an EV data example shown in Appendix A, that helps to understand how to calculate energy consumption, VKT in different periods of time and UR. The relationship between vehicle age and annual driving distance has been applied to simulate the life cycle VKT (see Appendix B [36]). See the **Supplementary** for specific parameters.

3.3.1. Usage pattern model

Previous studies on the LCA of EVs have primarily focused on precise calculations of vehicle production, electricity emissions, and related factors, while the usage of EVs has often been considered only from a macro-perspective through various statistical reports. This is sufficient to support the development direction of automotive technology and policy-specified rules, but in-depth analysis of real-world conditions is an important verification for evaluating such macro-statistics. Although most studies demonstrate that EVs have lower life-cycle emissions compared to conventional fuel vehicles, this advantage is constrained by the specific usage patterns of EVs. Thus, an interesting question arises: Which usage patterns enable EVs to reduce emissions, and which fail to achieve this in real-world conditions?

Many previous studies have applied many kinds of cluster or classification algorithms to recognise EV usage patterns [37–39]. In this paper, we establish the EV usage patterns based on RMF rules. The rule has often been used to classify and describe the potential value of users in marketing. This concept can also be shifted into the emission reduction potential capacity for EV users. Thus, when considering the Recency, we use daily VKT to represent the travel demand in one year; The UR of a year is used to describe the concept of the Frequency; While more energy consumption means more cost for using an EV, the energy consumption per 100 km (energy consumption/100 km) is calculated to represent the Monetary. In summary, daily VKT, UR and energy consumption are collected as the training features for the usage pattern clustering.

In the classification of the RMF, there are always two categories in each feature. However, in terms of EV usage in this paper, the number of categories is not limited to two, but it should not be excessive either, as too many dimensions can lead to overly complex cluster descriptions. The GMM model is used to cluster these features into different categories [1,39]. Many previous studies have applied a GMM model to classify EV usage features, because under large-scale samples, usage pattern characteristics tend to exhibit a combination of some normal distributions. The core function of GMM model is described in equation (3):

$$f(x) = \sum_{i=1}^{n}\left(A \times \frac{1}{\sqrt{2\pi}\sigma}e^{\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)}\right)_i, i \in I \tag{3}$$

where f (x) is the probability density of the feature x; μ means the average value of random variables subject to the normal distribution; σ^2 is the variance of a random variable; I is the index of the sub-distributions (categories) with i; and A is the weight of each category, because the sum of the probability is 100 %. Moreover, the Expectation Maximum (EM) algorithm is used to estimate the parameters in the GMM model.

3.3.2. Usage pattern features

(1) Energy consumption/100 km

Due to the limitations of data sampling, the energy consumption will be calculated by charging energy and driving distance rather than Ampere-Hour integral during the driving process. To measure the electricity consumed by EVs from the power grid per kilometre, we define the energy consumption of each trip as follows:

$$EC = \frac{E_c}{D_{trip}} \tag{4}$$

where D_{trip} is the driving distance of the trip and E_c is the charged energy in the adjacent charging process (the SOC intervals of the driving and charging processes are controlled to be the same). Thus, energy consumption results will vary across different driving sessions. The average value of all driving sessions will be used to calculate the annual energy consumption of one vehicle. Moreover, the fuel consumption benchmark of frugal ICEVs is set at 4.4 L/100 km [23]. The fuel consumption of a frugal ICEV is adjusted based on the ratio between the energy consumption of its corresponding frugal EV and the benchmark energy consumption derived from its battery capacity and AER.

(2) Annual- and Daily VKT

To incorporate real-world driving demand into the analysis, we extract the distributions of daily and annual driving distances using real-world records of EV operation. Since there may be more than one driving session in a day, multiple driving sessions for a vehicle are integrated to compute the daily driving distance. In this work, the daily VKT is obtained by calculating the difference between the last and first odometer values of the day. Then, daily VKT records are labelled with dates, regions, fleet types, and anonymous vehicle identifications to acquire daily driving distance sets in designated regions and of targeted fleet types. Annual driving distances are calculated by aggregating daily VKT. For both the daily and annual VKT, the cumulative distribution function F is shown in equation (5).

$$F(x) = \sum_{u=\varepsilon}^{x} f_{\Delta}(u) \tag{5}$$

where $f_{\Delta}(u)$ is the share of vehicles in the driving distance interval (u, $u + \Delta$], and ε is the threshold of the daily or monthly driving distance.

(3) Annual UR

Annual UR represents the usage intensity of the vehicle. Basically, more charging infrastructure construction and better battery performance can both improve consumer willingness to use EVs. The annual UR calculation is provided in equation (6).

$$\text{Annul UR} = \textit{Online Days}/365 \times 100\,\% \tag{6}$$

where *Online Days* represents the number of days the user uses the vehicle in a year.

3.3.3. Usage pattern recognition

(1) LDEV usage pattern clusters

Energy consumption per 100 km, daily VKT, and annual UR are used to establish the usage pattern model. In Fig. 3a, two distinct categories are identified: a low energy consumption category and a high energy consumption category, with average values centred around 7.94 kWh/100 km and 15.56 kWh/100 km, respectively, accounting for approximately two-thirds and one-third of the total. The majority of EVs exhibit relatively low consumption category, forming a solid basis for enhancing the emission reduction potential of LDV electrification. The daily VKT is divided into three categories (shown in Fig. 3b): low, medium, and high distances per day. This is a crucial factor in determining the lifetime VKT. The average distances for each class are 20.88 km, 46.14 km, and 91.78 km, with proportions of 60 %, 31 %, and 9 %, respectively. This indicates that most private LDEVs are used for short daily trips, making them more likely to be employed for daily commuting. The final indicator, annual UR can also be categorised into low and high groups, with average rates of 64 % and 92 % (see Fig. 3c). Over two-thirds of users operate their vehicles with a higher frequency of travel. Based on these three metrics (energy consumption, daily VKT, and UR), 12 possible LDEV usage patterns are defined (as shown in Table 3), though patterns with very low proportions are excluded from further analysis.

(2) Macro-usage patterns for frugal EVs

Table 4 provides parameters for the macro-usage patterns of frugal EVs under different electricity resource structures. The average temperature throughout the whole year in each province ranges from 15 °C to 20 °C, which is a suitable range for battery materials. However, there are still some significant differences in average energy consumption. The maximum energy consumption in the Midd-Clen-Self region is 0.72 kWh/100 km higher than the minimum value in the Tra-Import region. The highest average daily VKT, at 22.46 km, is found in the High-Clea-Export region, while the lowest, at 18.99 km, is in the Tra-Import region. The average annual UR fluctuates around 95 %. In most cases, average values are used to assess the emission reduction capacity of EV usage (see Table 5).

Table 3
LDEV usage pattern definitions.

Patterns	Descriptions
L-L-L	Low energy consumption; Low daily mileage; Low utilisation rate
L-M-L	Low energy consumption; Middle daily mileage; Low utilisation rate
L-H-L	Low energy consumption; High daily mileage; Low utilisation rate
H-L-L	High energy consumption; Low daily mileage; Low utilisation rate
H-M-L	High energy consumption; Middle daily mileage; Low utilisation rate
H-H-L	High energy consumption; High daily mileage; Low utilisation rate
L-L-H	Low energy consumption; Low daily mileage; High utilisation rate
L-M-H	Low energy consumption; Middle daily mileage; High utilisation rate
L-H-H	Low energy consumption; High daily mileage; High utilisation rate
H-L-H	High energy consumption; Low daily mileage; High utilisation rate
H-M-H	High energy consumption; Middle daily mileage; High utilisation rate
H-H-H	High energy consumption; High daily mileage; High utilisation rate

Table 4
The parameters for macro-usage patterns under different electricity resource structures.

Electricity patterns	Sample amount	Energy consumption (kWh/100 km)	Average daily VKT (km)	Average annual UR (%)
Tra-Export	11,292	8.98	20.98	95.0
Tra-Import	52,309	9.23	23.65	94.8
Midd-Clea-Export	4995	9.24	20.76	95.9
Midd-Clea-Self	8919	9.70	25.52	96.3
Midd-Clea-Import	7756	9.01	22.50	94.9
High-Clea-Export	9122	9.44	22.46	94.0

(3) Micro-usage patterns for frugal EVs

In terms of micro-usage patterns for frugal EVs, we only select micro-frugal EV usage patterns with more than 2 % proportion. Generally, the L-L-H pattern is the most common usage pattern for frugal EVs in China (ranging from 71 % to 79 %). The H-L-H pattern ranks second, ranging from 6 % to 11 %. H-M-H, L-L-L and L-M-H patterns also occupy a certain proportion. Specifically, the proportion of frugal EV usage patterns in six classical electricity patterns is shown as follows.

(1) Tra-Export: L-L-H (71 %), H-M-H (5 %), L-L-L (4 %), L-M-H (5 %) and H-L-H (6 %).
(2) Tra-Import: L-L-H (78 %), H-M-H (3 %), L-L-L (4 %), L-M-H (3 %) and H-L-H (11 %).
(3) Midd-Clea-Export: L-L-H (78 %), H-M-H (6 %), L-L-L (3 %), L-M-H (5 %) and H-L-H (6 %).

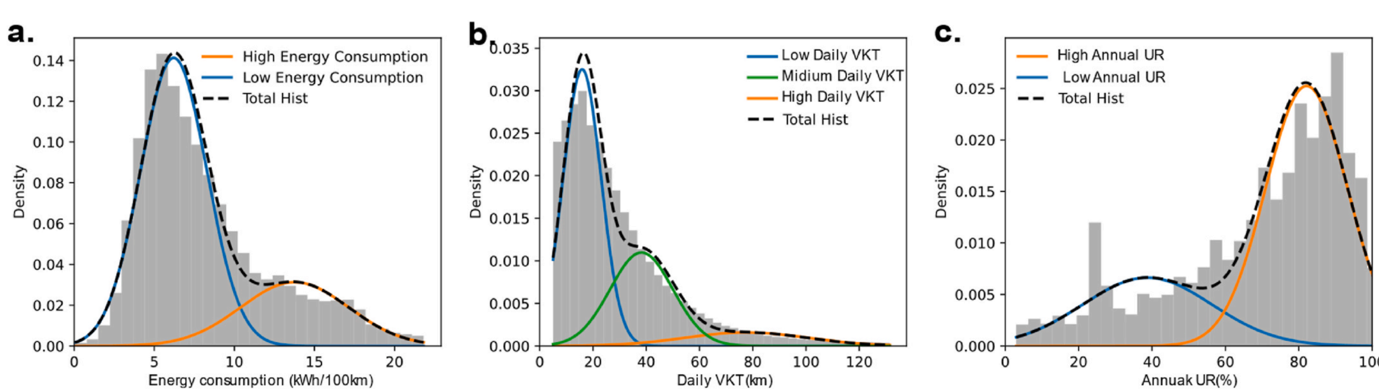

Fig. 3. Features of EV usage patterns. **a.** Energy consumption distributions. **b.** Daily VKT distributions. **c.** Annual UR distributions.

(4) Midd-Clea-Self: L-L-H (74 %), H-M-H (6 %), L-L-L (2 %), L-M-H (5 %) and H-L-H (10 %).
(5) Midd-Clea-Import: L-L-H (79 %), H-M-H (4 %), L-L-L (4 %), L-M-H (5 %) and H-L-H (7 %).
(6) High-Clea-Export: L-L-H (71 %), H-M-H (6 %), L-L-L (5 %), L-M-H (6 %) and H-L-H (9 %).

3.4. Disposal phase

Vehicle disposal for ICEV and EV (excluding battery) has been considered in the vehicle production phase, as part of the vehicle-ARD. The inventory for disposal of EV batteries is also obtained from the GREET software, measured in grams of emissions per tonne of battery cell recycling. Additionally, the number of battery replacements is considered in the disposal phase [15]. Generally, the battery replacement should consider both calendar ageing and cycle ageing. In most cases, if the state-of-health of the battery falls below 80 %, it is no longer deemed suitable for use in an EV [40]. Although 80 % of battery capacity can satisfy most daily travel demand of EV users, for the safe operation, most automobile manufacturers and the government in China still follow this rule. Consequently, one major battery replacement scheme for most automobile manufacturers is based on the cumulative driving mileage (i.e., cycle ageing), when it reaches 150,000 km (e.g., BYD Auto), 240,000 km (e.g., Tesla). Another rule (i.e., calendar ageing) always used is when the usage time reaches 8 years (e.g., BYD Auto, GEELY, BAIC). Before 2016, the value was 4 or 6 years [41]. Based on above two battery replacement schemes, this paper follows the battery replacement guideline provided by the Ministry of Finance of the People's Republic of China (http://www.gov.cn/xinwen/2015-04/29/content_2855040.htm): 120,000 km or 8 years. The scheme that meets the requirements first will be implemented as a priority.

4. Results and discussions

4.1. Emissions and reduction opportunities with macro-usage patterns

The emissions per 100 km, based on the macro-frugal EV usage patterns, are shown in Fig. 4. There are notable differences in emissions across the various electricity patterns, influenced by factors such as electricity sources, travel distances, and energy consumption per 100 km. Generally, emissions from traditional electricity sources are higher than those from clean energy sources, although some scenarios exhibit a different trend. To reduce the impact of outliers on the results, we calculated the median and its corresponding 95 % CI to represent the credible range of the results.

Based on macro-usage pattern features, CO_2 emissions of frugal EVs are significantly lower than that of frugal ICEVs (see Fig. 4a). Traditional electricity generation methods (Tra-Export and Tra-Import) still show higher emission trends than other electricity patterns. The CO_2 emissions of frugal EVs in Trd-Export and Tra-Import are 18.24 kg/100 km (95 %CI: 18.09–18.38) and 18.85 kg/100 km (95 % CI: 18.78–18.93), respectively, which is approximately 2.23 and 3.20 kg/100 km lower than the emissions of frugal ICEVs. In contrast, renewable electricity generation technologies demonstrate significant emission reductions. In the High-Clea-Export region, the CO_2 emissions of frugal EVs are 13.02 kg/100 km (95 % CI: 12.80–13.25), while frugal ICEV shows a significantly higher emission at 20.49 kg/100 km (95 % CI:20.36–20.64). This can be attributed to a higher reliance on clean energy sources, such as wind and solar power, in its electricity structure. In terms of VOC emissions (see Fig. 4b), previous studies have shown that LDPV electrification can reduce 98 % of emissions during the fuel cycle [42]. Even when considering the vehicle cycle, the VOC emissions of frugal EVs remain significantly lower than those of frugal ICEVs. Within all electricity patterns, the VOC emissions of frugal EVs reduce around 10 % compared to the frugal ICEVs. However, considering other emissions (i.

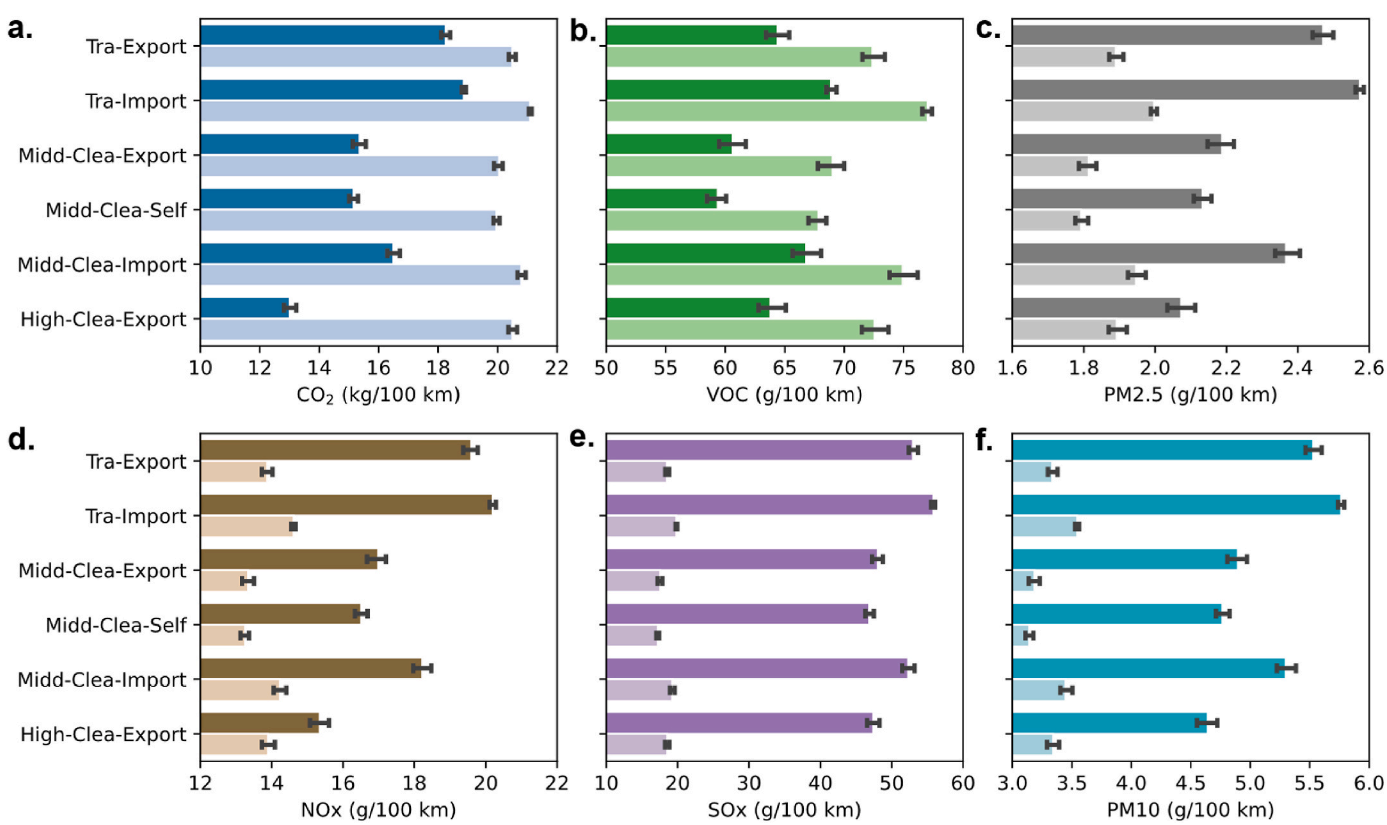

Fig. 4. Emissions per 100 km for frugal EV and ICEVs under different electricity resource structures. **a** CO_2, **b** VOC, **c** $PM_{2.5}$, **d** NO_x, **e** SO_x and **f** PM_{10}. The darker ones represent frugal EVs, while the lighter ones are frugal ICEVs.

e., $PM_{2.5}$, PM_{10}, NO_x and SO_x), there shows no advantages of frugal EVs. Cleaner electricity structure still has environmental benefits than traditional electricity structure, while the differences between frugal EVs and ICEVs are the smallest (see Fig. 4c–f). From a macro perspective, the environmental benefits during the use phase are not offset by those during the power system phase and vehicle battery production phase, while this doesn't mean that all frugal EVs don't have the opportunity to reduce emissions.

In terms of the electricity transfer path, export-oriented regions show lower emissions of all emission species compared to import-oriented regions. However, this does not mean that decarbonisation of the electricity grid is unnecessary. Comparing Tra-Export with Tra-Import, the latter benefits from a higher proportion of clean energy, as more clean energy is imported, contributing to a cleaner energy mix. Similarly, when comparing Midd-Clea-Export and Midd-Clea-Import, although both have 57 % of their electricity coming from traditional sources, the import of clean electricity from another province with over 50 % clean energy generation results in a cleaner energy profile.

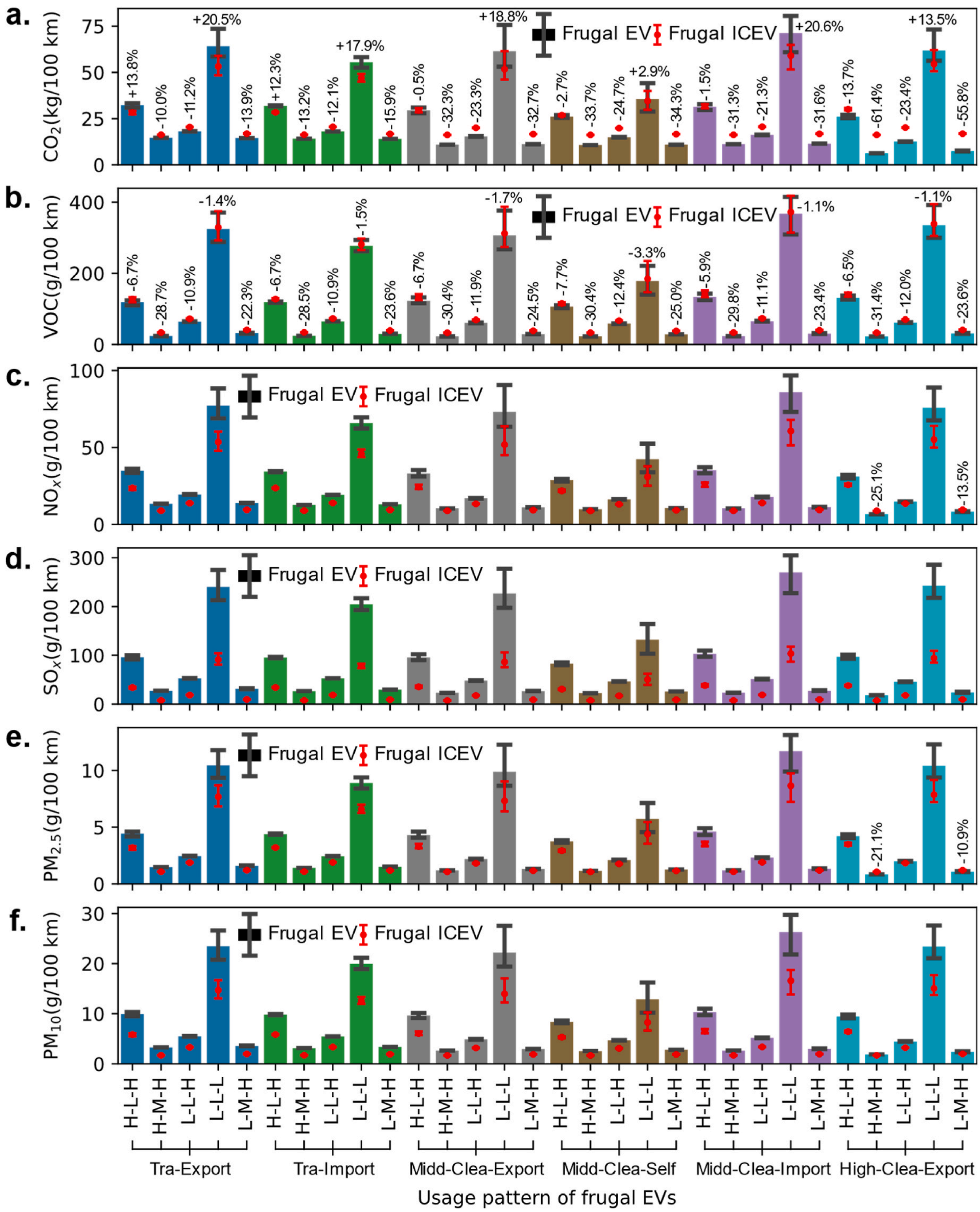

Fig. 5. Emissions reductions of frugal EV usage compared to counterpart ICEVs. **a** CO_2, **b** VOC, **c** NO_x, **d** SO_x, **e** $PM_{2.5}$ and **f** PM_{10}.

4.2. Emissions and reduction opportunities with micro-usage patterns

In this section, only usage patterns of frugal EVs with more than 2 % of the proportion are included to analyse the emissions and reduction opportunities. Frugal vehicle electrification can significantly reduce CO_2 (Fig. 5a) emissions in most patterns, except the L-L-L pattern in each region, and the H-L-H pattern in Tra-Import and Tra-Export regions, where the results of CO_2 emissions of frugal EVs are 32.39 kg/100 km (95 %CI: 30.95–33.46) and 31.93 kg/100 km (95 %CI: 31.61–32.26), while the results of frugal ICEVs are 28.30 kg/100 km (95 %CI: 27.48–29.12) and 28.43 kg/100 km (95 %CI: 28.20–28.66). Lack of vehicle usage (L-L-L usage pattern), especially with a higher energy consumption (H-L-H usage pattern), may lead to difficulties in reducing CO_2 emissions, especially in regions relying on traditional electricity generation. Due to the small amount of samples of L-L-L usage pattern, the range of 95 % CI is relatively larger than other usage patterns. It should also be noted that cleaner energy generation further enhances the environmental benefits of vehicle electrification. Analysing the '-Export'-based electricity patterns, the CO_2 emissions of H-L-H usage pattern in Midd-Clea-Export and High-Clea-Export decreases into 29.47 kg/100 km (95 %CI: 27.77–31.08) and 26.20 kg/100 km (95 %CI: 25.30–27.10). It should also be noted that patterns with a combination of '-M-H' exhibit greater potential for emission reductions, such as the 61.4 % reduction observed in the H-M-H pattern in the High-Clea-Export region. Longer life cycle VKT not only enhance the emission reduction period in the usage phase but also reduce the emissions from vehicle production or disposal every kilometre. Additionally, the emission reduction opportunities of the '-L-H' patterns are lower than the '-M-H' patterns, mainly caused by a lower life cycle VKT.

VOC emission reduction opportunities are significant in all electricity patterns with different frugal EV usage patterns, as shown in Fig. 5b. Even in L-L-L pattern, there is a drop of more than 1 %. A similar trend is observed for NO_x, SO_x, $PM_{2.5}$, and PM_{10} (Fig. 5c–f), where the life-cycle emissions of a frugal EV are no longer significantly lower than those of a frugal ICEV. In contrast, in the High-Clea-Export region, NO_x emissions show a substantial reduction under the H-M-H and L-M-H usage patterns, decreasing by 25.1 % and 13.5 %, respectively. Specifically, emissions drop from 8.85 g/100 km (95 % CI: 8.82–8.88) to 6.65 g/100 km (95 % CI: 6.56–6.66) for the H-M-H pattern and from 9.55 g/100 km (95 % CI: 9.42–9.71) to 8.23 g/100 km (95 % CI: 8.03–8.57) for the L-M-H pattern. A similar reduction is observed for $PM_{2.5}$. In the H-M-H usage pattern, emissions decrease from 1.069 g/100 km (95 % CI: 1.065–1.074) to 0.844 g/100 km (95 % CI: 0.837–0.852). Similarly, in the L-M-H usage pattern, emissions decline from 1.212 g/100 km (95 % CI: 1.190–1.242) to 1.081 g/100 km (95 % CI: 1.049–1.125) in the High-Clea-Export region. Although the energy consumption of the H-M-H pattern is a little higher than that of the L-M-H pattern, the life-cycle VKT is 1.5 times higher than that of L-M-H, resulting in a similar emission reduction but more reduction proportion of the H-M-H.

We compare the emission proportions of a frugal EV and an ICEV with different usage patterns in different phases of the LCA to illustrate the changes in the impact of the vehicle usage on the emission reduction, as shown in Table 5. Under macro usage patterns, frugal EVs outperform frugal ICEVs in most pollutant emissions, but their performance is influenced by the electricity mix. In the High-Clea-Export region, the CO_2 emissions of frugal EVs during the WtW are only 12.8 %, significantly lower than the 57.2 % of frugal ICEVs. Additionally, pollutants such as $PM_{2.5}$(5.8 % vs. 26.0 %) and NO_x (8.2 % vs. 30.4 %) are also significantly reduced, demonstrating the great emission reduction potential clean electricity. However, in the Tra-Export scenario, the CO_2 emissions of frugal EVs during the WtW rise to 37.3 %, though still lower than frugal ICEVs (57.8 %), while SO_x emissions (15.0 % vs. 4.7 %) exceed those of frugal ICEVs, indicating that a high proportion of coal-fired power may weaken the emission reduction opportunities of frugal EVs for certain pollutants. Additionally, battery contributes significantly to $PM_{2.5}$ (16.1 %) and SO_x (38.7 %) emissions, highlighting the importance of optimising battery production.

Frugal EV emissions are influenced by both electricity patterns and usage patterns. For H-L-H and H-M-H usage patterns, WtW CO_2 emissions of EVs decrease significantly under a clean power grid. For example, under the High-Clea-Export scenario, the WtW CO_2 emissions of frugal EVs in the H-L-H pattern account for only 9.7 %, which is much lower than the 44.5 % of frugal ICEVs, demonstrating a clear carbon reduction advantage. However, in Tra-Export and Tra-Import regions, the high carbon intensity of electricity used for frugal EV charging significantly increases CO_2 emissions. In the Tra-Export scenario, the WtW CO_2 emissions of frugal EVs in the H-M-H pattern reach 71.8 %, close to the 82.2 % of frugal ICEVs. For L-L-H, L-L-L, and L-M-H usage patterns, the proportions of CO_2, PM, and NO_x emissions from frugal EVs are generally lower than those from frugal ICEVs. For instance, under the High-Clea-Export scenario, the WtW CO_2 emissions of EVs in the L-L-L pattern account for only 2.6 %, compared to 24.8 % for ICEVs, highlighting significant carbon reduction benefits. However, in traditional electricity structure, SO_x emissions from battery manufacturing and electricity generation may weaken the environmental benefits of EVs. In the Tra-Export scenario, the WtW SO_x emissions of frugal EVs in the L-L-H pattern account for 13.6 %, while the battery-related SO_x emissions reach 39.3 %, indicating that battery production plays a significant role in total emissions. Overall, in regions with more traditional fossil electricity generation, optimising battery production and improving grid cleanliness are particularly crucial.

4.3. Trade-off between frugal EVs and ICEVs

The emission trade-off period in CO_2 and VOC emissions, in all electricity patterns and $PM_{2.5}$ and NO_x in High-Clea-Export region are provided in Fig. 6. The proportion of frugal EVs with emissions reduction is shown above the red line, while the bar below this line represents the emissions from frugal EVs are higher than those from frugal ICEVs. Vehicle age has a strong relation with life cycle VKT [43], while longer vehicle usage age with longer mileage can offset the emission from vehicle and battery production of frugal EVs which is higher than that of the frugal ICEVs. In general, the effort of clean electricity generation is still obvious. In Tra-Export and Tra-Import regions, the trade-off cannot be reached before 3-year vehicle usage, while in High-Clea-Export scenario, about 3.3 % frugal EVs have achieved the CO_2 emission reduction advantages. Based on the focus of 12-year vehicle age in this paper, about 79 % of frugal EVs can achieve the CO_2 emission reduction compared to frugal ICEVs. In terms of specific electricity patterns, the proportions of CO_2 emission reduction are 78.4 %, 75.1 %, 88.0 %, 89.3 %, 83.8 % and 89.1 % in the electricity patterns from the left side to the right in Fig. 6a, respectively. In terms of reduction proportion of each usage patterns, more than 95 % frugal EVs with H-M-H and L-M-H usage patterns achieve the CO_2 emission reduction compared to the frugal ICEVs. The L-L-H usage pattern is the main part of the frugal EVs, where the maximum proportion of Tra-Export reaches 95.0 % and the minimum proportion of High-Clea-Export is 85.1 %. In contrast, even over the longest assessment period of 20 years, the proportions of non-emission reduction of H-L-H and L-L-L remain significant. The results of H-L-H are around 95.0 % in traditional electricity regions. The proportion of L-L-L are around 45.1 %–75.7 % of the total in each electricity pattern. Moreover, VOC emissions reduction proportion can reach more than 95 % about 4–6 years, due to the high emission proportion in WtW phase of the frugal ICEVs (see Fig. 6b). In terms of other emissions, only $PM_{2.5}$ and NO_x in High-Clea-Export show an emission reduction opportunity, while there are no reduction opportunities of SO_x and PM_{10} in all electricity patterns. The $PM_{2.5}$ emission reduction can reach the balance in the second year, while the proportion in 12-year vehicle usage is about 30.0 %, and the final proportion with reduction opportunities in 20-year vehicle usage can reach about 44.2 %. Similar trends of NOx emission reduction can be found in Fig. 6d, where the emissions reduction proportion of the balance year, 12 year and the end

Table 5
Emissions proportion of the WtW and battery for frugal EVs and ICEVs.

Emissions	Usage pattern	Tra-Export (%)			Tra-Import (%)			Midd-Clea-Export (%)			Midd-Clea-Self (%)			Midd-Clea-Import (%)			High-Clea-Export (%)		
		EV		ICEV	EV		ICEV	EV		ICEV	EV		ICEV	EV		ICEV	EV		ICEV
		WtW	Battery	WtW	WtW	Battery	WtW	WtW	Battery	WtW	WtW	Battery	WtW	WtW	Battery	WtW	WtW	Battery	WtW
CO_2	Macro	37.3	16.0	57.8	35.3	16.5	56.5	30.6	17.7	59.3	31.2	17.6	60.3	28.5	18.3	56.6	12.8	22.3	57.2
	H-L-H	35.2	16.6	47.6	33.4	17.0	46.8	24.9	19.2	45.4	27.5	18.5	49.3	24.2	19.4	43.8	9.7	23.1	44.5
	H-M-H	71.8	7.2	82.2	70.3	7.6	81.7	63.1	9.4	82.3	62.3	9.6	82.1	63.0	9.4	81.8	34.8	16.7	81.7
	L-L-H	35.8	16.4	58.1	34.7	16.7	57.9	28.5	18.3	59.4	29.0	18.2	60.5	27.3	18.6	57.5	11.7	22.6	58.7
	L-L-L	10.5	22.9	25.1	12.5	22.4	29.1	8.1	23.5	25.8	12.2	22.4	35.2	7.3	23.7	23.6	2.6	24.9	24.8
	L-M-H	54.3	11.7	72.1	55.7	11.3	73.8	46.3	13.7	73.6	47.5	13.4	74.7	45.8	13.9	72.8	20.8	20.2	71.7
VOC	Macro	Macro	1.2	1.3	14.2	1.0	1.3	13.3	0.8	1.3	15.0	0.8	1.3	15.5	0.7	1.3	13.7	0.2	1.3
	H-L-H	H-L-H	1.0	1.3	10.1	0.8	1.3	9.5	0.6	1.3	9.2	0.6	1.3	10.5	0.5	1.3	8.7	0.2	1.3
	H-M-H	H-M-H	4.1	1.2	33.4	3.6	1.2	32.7	2.8	1.2	33.8	2.5	1.2	33.8	2.6	1.2	33.3	0.8	1.3
	L-L-H	L-L-H	1.0	1.3	13.4	0.9	1.3	13.3	0.7	1.3	14.0	0.7	1.3	14.5	0.6	1.3	13.1	0.2	1.3
	L-L-L	L-L-L	0.2	1.3	3.8	0.2	1.3	4.6	0.2	1.3	3.8	0.2	1.3	6.0	0.1	1.3	3.4	0.0	1.3
	L-M-H	L-M-H	2.1	1.2	22.4	2.1	1.2	23.6	1.5	1.3	23.5	1.4	1.3	24.5	1.4	1.3	22.8	0.4	1.3
PM_{10}	Macro	21.8	15.0	18.1	19.3	15.5	17.0	16.7	16.0	19.1	16.1	16.1	19.7	14.8	16.4	17.4	5.4	18.2	18.3
	H-L-H	19.8	15.4	14.0	17.7	15.8	13.2	12.8	16.7	12.7	13.5	16.6	14.5	11.9	16.9	12.1	4.0	18.4	12.4
	H-M-H	52.4	9.1	41.9	49.2	9.7	41.2	42.2	11.1	42.5	39.7	11.6	42.4	41.1	11.3	41.8	16.7	16.0	41.7
	L-L-H	20.1	15.3	17.0	18.6	15.6	16.8	15.0	16.3	17.8	14.3	16.4	18.4	13.7	16.6	16.7	4.8	18.3	17.5
	L-L-L	5.1	18.2	4.7	5.9	18.1	5.8	3.7	18.5	4.9	5.4	18.2	7.7	3.2	18.6	4.4	1.0	19.0	4.6
	L-M-H	34.9	12.5	28.4	34.8	12.5	29.8	27.4	13.9	29.7	26.8	14.0	31.0	26.1	14.2	28.8	9.1	17.5	28.0
$PM_{2.5}$	Macro	22.1	16.1	25.9	19.5	16.7	24.6	17.0	17.2	27.1	16.6	17.3	27.9	15.1	17.6	25.0	5.8	19.5	26.0
	H-L-H	20.1	16.6	19.9	17.9	17.0	19.1	13.0	18.0	18.3	13.9	17.8	20.8	12.2	18.2	17.5	4.2	19.8	17.9
	H-M-H	52.8	9.8	53.2	49.6	10.4	52.5	42.8	11.9	53.7	40.5	12.3	53.6	41.7	12.1	53.0	17.6	17.1	52.9
	L-L-H	20.4	16.5	24.9	18.8	16.8	24.7	15.2	17.6	25.9	14.7	17.7	26.7	14.0	17.8	24.4	5.1	19.7	25.5
	L-L-L	5.2	19.6	7.5	5.9	19.5	9.2	3.8	19.9	7.8	5.6	19.6	11.9	3.3	20.0	7.0	1.1	20.5	7.4
	L-M-H	35.3	13.4	38.7	35.1	13.4	40.4	27.8	15.0	40.3	27.5	15.0	41.7	26.6	15.2	39.3	9.6	18.7	38.2
NO_x	Macro	28.6	19.4	30.2	25.8	20.2	29.0	22.7	21.0	31.7	22.2	21.1	32.7	20.3	21.7	29.2	8.2	25.0	30.4
	H-L-H	26.5	20.0	25.3	23.9	20.7	24.4	17.9	22.3	23.4	19.0	22.0	26.4	16.7	22.6	22.3	6.0	25.5	22.9
	H-M-H	62.1	10.3	60.9	59.1	11.1	60.2	52.4	12.9	61.4	50.0	13.6	61.2	51.2	13.3	60.7	23.9	20.7	60.5
	L-L-H	26.9	19.9	29.0	25.1	20.4	28.8	20.7	21.5	30.1	20.1	21.7	31.1	19.1	22.0	28.5	7.3	25.2	29.8
	L-L-L	7.3	25.2	8.7	8.3	24.9	10.6	5.5	25.7	9.2	7.9	25.0	14.0	4.7	25.9	8.2	1.5	26.8	8.6
	L-M-H	44.0	15.2	44.8	43.9	15.2	46.8	36.0	17.4	46.5	35.6	17.5	48.3	34.6	17.8	45.5	13.5	23.5	44.3
SO_x	Macro	15.0	38.7	4.7	13.1	39.6	4.3	11.2	40.4	5.0	10.8	40.6	5.3	9.9	41.0	4.4	3.5	44.0	4.8
	H-L-H	13.4	39.4	3.9	11.7	40.2	3.6	8.3	41.7	3.5	8.8	41.5	4.1	7.8	42.0	3.3	2.5	44.4	3.4
	H-M-H	40.3	27.2	14.7	37.3	28.6	14.3	30.9	31.5	15.1	28.9	32.4	15.1	30.0	31.9	14.7	11.0	40.5	14.6
	L-L-H	13.6	39.3	4.1	12.4	39.9	4.0	9.8	41.1	4.3	9.4	41.2	4.5	9.0	41.4	3.9	3.0	44.2	4.2
	L-L-L	3.2	44.0	0.9	3.7	43.8	1.1	2.3	44.5	1.0	3.4	44.0	1.6	2.0	44.6	0.9	0.6	45.2	0.9
	L-M-H	25.0	34.1	8.1	24.8	34.2	8.7	18.8	36.9	8.6	18.5	37.1	9.1	18.0	37.3	8.2	5.8	42.9	8.0

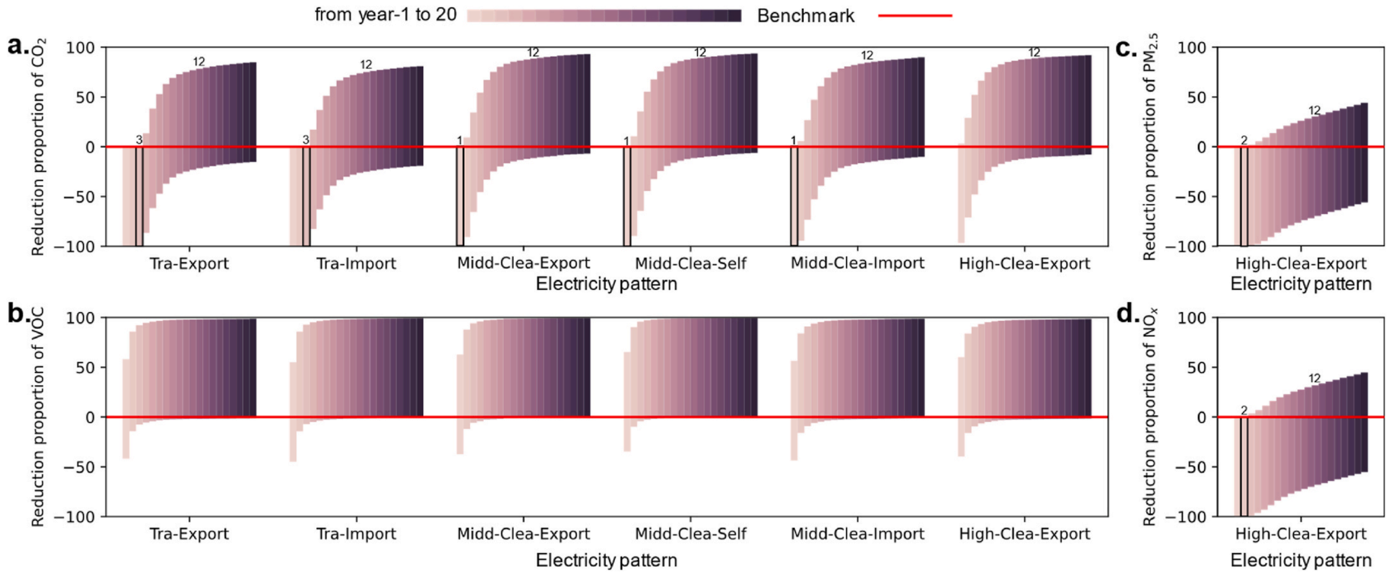

Fig. 6. Emission trade-off period of replacing a frugal ICEV into a frugal EV. **a** CO_2; **b** $PM_{2.5}$ in High-Clea-Export region; **c** VOC and **d** NO_x in High-Clea-Export region.

year of the assessment is 2, 30.3 % and 44.7 %, respectively. The usage patterns in '-M-H' are still the main elements of emission reductions as well as trend in CO_2 emissions.

4.4. Discussions

The results highlight that frugal EVs, especially in regions with a cleaner electricity grid, offer significant reductions in CO_2 [18], which can be found in the **Supplementary** Excel file. While VOC emissions are also benefits from the frugal ICEV electrification, the fluids contribute the most part, which is similar with the results in Ref. [44]. Moreover, the benefits of other emissions are not uniform across all regions, as the varying electricity mix and battery production emissions play a crucial role in determining the overall environmental impact. Based on previous studies in China, EVs do not yet possess a full life cycle advantage in reducing primary $PM_{2.5}$ and SO_x emissions, mainly due to emissions from upstream coal-fired electricity generation and the production processes of battery materials [30,45]. It can be seen that the largest differences in $PM_{2.5}$ and SO_x emissions between frugal EVs and counterpart ICEVs occur during the Well-to-Tank and Tank-to-Wheel phases, with batteries remaining the main contributing factor (see the **Supplementary**). Previous studies have also pointed out that, for example, in northern China where the power system is primarily coal-based, the use of EVs still does not guarantee significant reductions in NO_x emissions [18,44,45]. This is evident in the Tra-Import and Tra-Export regions, where frugal EVs exhibit higher NO_x emissions than their ICEV counterparts during the WtW phase. Therefore, based on the results **in** Fig. 5c and the contribution of the NO_x emission, it can be concluded that clean electricity generation mix is an absolute prerequisite for achieving this enormous reduction potential of EVs.

The subsidy policy for EVs has gradually shifted towards longer AER models with high-energy-density batteries, resulting in the reduction of financial support for shorter AER EVs. While this adjustment has promoted the development of longer AER EVs, it has also imposed certain limitations on the growth of frugal EVs. Without subsidy support, the economic attractiveness of such vehicles may be reduced, which in turn affects market promotion. In this study, we demonstrate the potential of frugal EVs to contribute to emission reductions across various provinces with different electricity mix structures. Additionally, actively driving an EV rather than leaving it parked in the garage helps to offset the additional emissions associated with battery production and recycling [46,47]. Another key finding is that short daily travel with a high utilisation rate is the most common pattern of frugal EV usage, which is in line with the design aim of this kind of vehicle. In contrast, lower intensity usage pattern may limit the overall emission reduction potential, as these vehicles spend a larger portion of their lifespan with underutilised capacity. It might be the example of a short AER EV replacing one ICEV of a two-car household [48] or privately operated short-distance shared vehicle services [49]. However, if in order to get the purchase subsides to develop longer AER vehicle model may result in a waste of battery materials, because some frugal vehicle scenarios may not require such a large battery capacity. Therefore, to maximise emission reduction opportunities, implementing personal carbon trading could incentivise EV usage by encouraging consumers to choose energy-efficient options, thereby indirectly promoting frugal EV adoption [3]. In other words, this approach could leverage the fact that frugal EVs have lower life cycle emissions than other LDEV segments in short AER scenarios [18,50] and encourage users with low daily VKT and low utilisation rates ('-L-L'/'-L-H' usage patterns) to use vehicles.

There are still some considerations that can be addressed in the future studies. First, we only collect the EV operation data. The user attributes and preferences are important to realise the detailed usage pattern, which can be addressed in the future studies. The comparisons between frugal EVs and other sized LDEVs can be addressed in the future work. Since frugal EV has an advantage in total owner cost, the double-win both in economy and environment may be suitable for some EV users with lower intensity usage patterns. Moreover, as the emissions from non-exhaust $PM_{2.5}$ emissions are becoming increasingly concerning [51], it can be addressed in the future studies. In particular, the regenerative braking system of EVs effectively reduces the formation of brake wear particles [52], which may result in somewhat different emissions between EVs and ICEVs. Finally, the battery replacement scheme of 80 % SOH considering the battery safety may be upgraded combining with the usage patterns, which can improve the environment benefits of vehicle electrification.

5. Conclusions

This study systematically analyses the environmental impact of frugal EVs using the LCA method, based on large-scale real-world EV operation data. A GMM-based usage pattern recognition method is developed, integrating different regional electricity structures to comprehensively evaluate the emission reduction potential of frugal EVs. The results indicate that over 70 % of frugal EV users travel short daily distances with low energy consumption, aligning with the design intent of these vehicles. However, different usage patterns have a significant impact on emission reduction. High-utilisation users (e.g., H-M-H pattern) can offset the additional emissions from battery production more quickly, achieving greater reductions in CO_2 emissions. In contrast, low-utilisation users (e.g., L-L-L pattern) may result in lower overall emission reduction benefits and, in some cases, may even fail to effectively reduce CO_2 emissions. Additionally, the study finds that while frugal EVs have a clear advantage in reducing VOC emissions, their reductions in NO_x, SO_x, $PM_{2.5}$ and PM_{10} emissions depend heavily on electricity structure and battery production impact. Furthermore, this study explores the emission trade-off point between frugal EVs and ICEVs. The findings show that in regions with a high proportion of clean electricity (e.g., High-Clea-Export pattern), frugal EVs can achieve CO_2 emission parity in a shorter time, whereas in regions with a higher share of coal-fired electricity (e.g., Tra-Export pattern), it takes longer to gain an emission advantage. Moreover, the study highlights that battery production contributes significantly to PM and SO_x emissions, underscoring the importance of optimising battery manufacturing processes to further enhance the environmental benefits of frugal EVs.

CRediT authorship contribution statement

Dingsong Cui: Writing – original draft, Methodology, Investigation. **Haibo Chen:** Project administration, Funding acquisition, Conceptualization. **David Watling:** Writing – original draft, Conceptualization. **Ye Liu:** Investigation, Conceptualization. **Jin Liu:** Project administration. **Chenxi Wang:** Investigation. **Mengyuan Xu:** Resources, Methodology. **Shuo Wang:** Funding acquisition, Formal analysis. **Zhenpo Wang:** Supervision. **Chengcheng Xu:** Investigation.

Declaration of competing interest

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

Acknowledgements

This work was part of the ZEV-UP project co-funded by the European Union under Grant agreement ID: 101138721. ZEV-UP aims to develop cost-effective and user-friendly EVs for both passenger and goods transportation. Views and opinions expressed are, however, those of the author(s) only and do not necessarily reflect those of the European Union or European Climate, Infrastructure and Environment Executive Agency (CINEA). Neither the European Union nor the granting authority can be held responsible for them. This work was also sponsored by Beijing Nova Program under grant 20220484105.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2025.137823.

Data availability

The authors do not have permission to share data.

References

[1] Cui D, Wang Z, Liu P, Wang S, Zhang Z, Dorrell DG, et al. Battery electric vehicle usage pattern analysis driven by massive real-world data. Energy 2022;250:123837. https://doi.org/10.1016/j.energy.2022.123837.
[2] Li X, Wang Z, Zhang L, Sun F, Cui D, Hecht C, Figgener J, Sauer DU. Electric vehicle behavior modeling and applications in vehicle-grid integration: an overview. Energy 2023;268:126647.
[3] Zhan W, Wang Z, Deng J, Liu P, Cui D. Integrating system dynamics and agent-based modeling: a data-driven framework for predicting electric vehicle market penetration and GHG emissions reduction under various incentives scenarios. Appl Energy 2024;372:123749. https://doi.org/10.1016/j.apenergy.2024.123749.
[4] Zhao Y, Wang Z, Shen Z-JM, Sun F. Assessment of battery utilization and energy consumption in the large-scale development of urban electric vehicles. Proc Natl Acad Sci 2021;118:e2017318118. https://doi.org/10.1073/pnas.2017318118.
[5] Milovanoff A, Posen ID, MacLean HL. Electrification of light-duty vehicle fleet alone will not meet mitigation targets. Nat Clim Change 2020;10:1102–7. https://doi.org/10.1038/s41558-020-00921-7.
[6] Chen H, Can Sener SE, Van Emburg C, Jones M, Bogucki T, Bonilla N, et al. Electric light-duty vehicles have decarbonization potential but may not reduce other environmental problems. Commun Earth Environ 2024;5:476. https://doi.org/10.1038/s43247-024-01608-z.
[7] Das PK, Bhat MY, Sajith S. Life cycle assessment of electric vehicles: a systematic review of literature. Environ Sci Pollut Res 2023;31:73–89. https://doi.org/10.1007/s11356-023-30999-3.
[8] Verma S, Dwivedi G, Verma P. Life cycle assessment of electric vehicles in comparison to combustion engine vehicles: a review. Mater Today Proc 2022;49:217–22. https://doi.org/10.1016/j.matpr.2021.01.666.
[9] Nakamoto Y, Tokito S, Hanaka T. Strategic roadmap for optimising vehicle emission reductions and electrification. Environ Res Lett 2024;19:054016. https://doi.org/10.1088/1748-9326/ad3b25.
[10] Liu X, Zhao F, Geng J, Hao H, Liu Z. Comprehensive assessment for different ranges of battery electric vehicles: is it necessary to develop an ultra-long range battery electric vehicle? iScience 2023;26:106654. https://doi.org/10.1016/j.isci.2023.106654.
[11] Rainieri G, Buizza C, Ghilardi A. The psychological, human factors and socio-technical contribution: a systematic review towards range anxiety of battery electric vehicles' drivers. Transport Res F Traffic Psychol Behav 2023;99:52–70. https://doi.org/10.1016/j.trf.2023.10.001.
[12] Qiao Q, Zhao F, Liu Z, Hao H, He X, Przesmitzki SV, et al. Life cycle cost and GHG emission benefits of electric vehicles in China. Transp Res Part Transp Environ 2020;86:102418. https://doi.org/10.1016/j.trd.2020.102418.
[13] Wu Z, Wang M, Zheng J, Sun X, Zhao M, Wang X. Life cycle greenhouse gas emission reduction potential of battery electric vehicle. J Clean Prod 2018;190:462–70. https://doi.org/10.1016/j.jclepro.2018.04.036.
[14] Huang Y, Jiang L, Chen H, Dave K, Parry T. Comparative life cycle assessment of electric bikes for commuting in the UK. Transp Res Part Transp Environ 2022;105:103213. https://doi.org/10.1016/j.trd.2022.103213.
[15] Ambrose H, Kendall A, Lozano M, Wachche S, Fulton L. Trends in life cycle greenhouse gas emissions of future light duty electric vehicles. Transp Res Part Transp Environ 2020;81:102287. https://doi.org/10.1016/j.trd.2020.102287.
[16] Habla W, Huwe V, Kesternich M. Electric and conventional vehicle usage in private and car sharing fleets in Germany. Transp Res Part Transp Environ 2021;93:102729. https://doi.org/10.1016/j.trd.2021.102729.
[17] Wei F, Walls WD, Zheng X, Li G. Evaluating environmental benefits from driving electric vehicles: the case of Shanghai, China. Transp Res Part Transp Environ 2023;119:103749. https://doi.org/10.1016/j.trd.2023.103749.
[18] Li W, Long R, Chen H, Wang M, Li Q, Wu M, et al. Inter-provincial emissions transfer embodied in electric vehicles in China. Transp Res Part Transp Environ 2023;119:103756. https://doi.org/10.1016/j.trd.2023.103756.
[19] Zhao P, Zhang S, Santi P, Cui D, Wang F, Liu P, et al. Challenges and opportunities in truck electrification revealed by big operational data. Nat Energy 2024. https://doi.org/10.1038/s41560-024-01602-x.
[20] Calearo L, Marinelli M, Ziras C. A review of data sources for electric vehicle integration studies. Renew Sustain Energy Rev 2021;151:111518. https://doi.org/10.1016/j.rser.2021.111518.
[21] Faria R, Marques P, Moura P, Freire F, Delgado J, De Almeida AT. Impact of the electricity mix and use profile in the life-cycle assessment of electric vehicles. Renew Sustain Energy Rev 2013;24:271–87. https://doi.org/10.1016/j.rser.2013.03.063.
[22] Girardi P, Brambilla PC. Electric cars vs diesel and gasoline: a comparative LCA ranging from micro-car to family car. Mod Environ Sci Eng 2019;5:125–36.
[23] Helmers E, Dietz J, Hartard S. Electric car life cycle assessment based on real-world mileage and the electric conversion scenario. Int J Life Cycle Assess 2017;22:15–30. https://doi.org/10.1007/s11367-015-0934-3.
[24] Zhang B, Lu Q, Wu P. Study on life-cycle energy impact of new energy vehicle car-sharing with large-scale application. J Energy Storage 2021;36:102334. https://doi.org/10.1016/j.est.2021.102334.
[25] 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. https://doi.org/10.1016/j.jenvman.2021.114050.
[26] Chen W, Sun X, Liu L, Liu X, Zhang R, Zhang S, et al. Carbon neutrality of China's passenger car sector requires coordinated short-term behavioral changes and long-term technological solutions. One Earth 2022;5:875–91. https://doi.org/10.1016/j.oneear.2022.07.005.
[27] Nakamoto Y, Tokito S, Kito M. Impact of vehicle electrification on global supply chains and emission transfer. Environ Res Lett 2023;18:054021. https://doi.org/10.1088/1748-9326/acd074.
[28] Lu Y, Liu Q, Li B, Jiang Q, Li Q. Energy mix-driven dynamic life cycle assessment on greenhouse gas emissions of passenger cars in China. J Clean Prod 2024;466:142817. https://doi.org/10.1016/j.jclepro.2024.142817.
[29] Xia X, Li P, Xia Z, Wu R, Cheng Y. Life cycle carbon footprint of electric vehicles in different countries: a review. Sep Purif Technol 2022;301:122063. https://doi.org/10.1016/j.seppur.2022.122063.

[30] Yang L, Yu B, Yang B, Chen H, Malima G, Wei Y-M. Life cycle environmental assessment of electric and internal combustion engine vehicles in China. J Clean Prod 2021;285:124899. https://doi.org/10.1016/j.jclepro.2020.124899.
[31] Edkins J. Are electric cars heavier than petrol cars?. https://www.carwow.co.uk/editorial/going-electric/ev-tips-and-advice/are-electric-cars-heavier-than-petrol-and-diesel-cars; 2023.
[32] Li L, Yue C, Ma S, Ma X, Gao F, Zheng Y, et al. Life cycle assessment of car energy transformation: evidence from China. Ann Oper Res 2023. https://doi.org/10.1007/s10479-023-05736-1.
[33] Zhang X, Patino-Echeverri D, Li M, Wu L. A review of publicly available data sources for models to study renewables integration in China's power system. Renew Sustain Energy Rev 2022;159:112215. https://doi.org/10.1016/j.rser.2022.112215.
[34] Wang J, Song C, Yuan R. CO2 emissions from electricity generation in China during 1997–2040: the roles of energy transition and thermal power generation efficiency. Sci Total Environ 2021;773:145026. https://doi.org/10.1016/j.scitotenv.2021.145026.
[35] Shang H, Sun Y, Huang D, Meng F. Life cycle assessment of atmospheric environmental impact on the large-scale promotion of electric vehicles in China. Resour Environ Sustain 2024;15:100148. https://doi.org/10.1016/j.resenv.2024.100148.
[36] Sun S, Sun L, Liu G, Zou C, Wang Y, Wu L, et al. Developing a vehicle emission inventory with high temporal-spatial resolution in Tianjin, China. Sci Total Environ 2021;776:145873. https://doi.org/10.1016/j.scitotenv.2021.145873.
[37] Zhang J, Wang Z, Miller EJ, Cui D, Liu P, Zhang Z. Charging demand prediction in Beijing based on real-world electric vehicle data. J Energy Storage 2023;57:106294. https://doi.org/10.1016/j.est.2022.106294.
[38] Lyu W, Hu Y, Liu J, Chen K, Liu P, Deng J, et al. Impact of battery electric vehicle usage on air quality in three Chinese first-tier cities. Sci Rep 2024;14:21. https://doi.org/10.1038/s41598-023-50745-6.
[39] Helmus JR, Lees MH, Van Den Hoed R. A data driven typology of electric vehicle user types and charging sessions. Transport Res C Emerg Technol 2020;115:102637. https://doi.org/10.1016/j.trc.2020.102637.
[40] Zhou L, Zhang Z, Liu P, Zhao Y, Cui D, Wang Z. Data-driven battery state-of-health estimation and prediction using IC based features and coupled model. J Energy Storage 2023;72:108413. https://doi.org/10.1016/j.est.2023.108413.
[41] Ren Y, Sun X, Wolfram P, Zhao S, Tang X, Kang Y, et al. Hidden delays of climate mitigation benefits in the race for electric vehicle deployment. Nat Commun 2023;14:3164. https://doi.org/10.1038/s41467-023-38182-5.
[42] Zheng Y, He X, Wang H, Wang M, Zhang S, Ma D, et al. Well-to-wheels greenhouse gas and air pollutant emissions from battery electric vehicles in China. Mitig Adapt Strategies Glob Change 2020;25:355–70. https://doi.org/10.1007/s11027-019-09890-5.
[43] Kito M, Nakamoto Y, Kagawa S, Hienuki S, Hubacek K. Environmental consequences of Japan's ban on sale of new fossil fuel-powered passenger vehicles from 2035. J Clean Prod 2024;437:140658. https://doi.org/10.1016/j.jclepro.2024.140658.
[44] Shi S, Zhang H, Yang W, Zhang Q, Wang X. A life-cycle assessment of battery electric and internal combustion engine vehicles: a case in Hebei Province, China. J Clean Prod 2019;228:606–18. https://doi.org/10.1016/j.jclepro.2019.04.301.
[45] Wang L, Yu Y, Huang K, Zhang Z, Li X. The inharmonious mechanism of CO2, NOx, SO2, and PM2.5 electric vehicle emission reductions in Northern China. J Environ Manag 2020;274:111236. https://doi.org/10.1016/j.jenvman.2020.111236.
[46] Nunes A, Woodley L. Governments should optimize electric vehicle subsidies. Nat Hum Behav 2023;7:470–1. https://doi.org/10.1038/s41562-023-01557-1.
[47] Nunes A, Woodley L, Rossetti P. Re-thinking procurement incentives for electric vehicles to achieve net-zero emissions. Nat Sustain 2022;5:527–32. https://doi.org/10.1038/s41893-022-00862-3.
[48] Jakobsson N, Sprei F, Karlsson S. How do users adapt to a short-range battery electric vehicle in a two-car household? Results from a trial in Sweden. Transp Res Interdiscip Perspect 2022;15:100661. https://doi.org/10.1016/j.trip.2022.100661.
[49] Lee H, Kim J, Seo S, Sim M, Kim J. Exploring behaviors and satisfaction of micro-electric vehicle sharing service users: evidence from a demonstration project in Jeju Island, South Korea. Sustain Cities Soc 2022;79:103673. https://doi.org/10.1016/j.scs.2022.103673.
[50] Zhang H, Zhao F, Hao H, Liu Z. Comparative analysis of life cycle greenhouse gas emission of passenger cars: a case study in China. Energy 2023;265:126282. https://doi.org/10.1016/j.energy.2022.126282.
[51] Liu Y, Chen H, Jiang L, Li T, Guo J, Wei T, et al. Environmental and health impacts of banning passenger cars with internal combustion engines: a case study of Leeds, UK. Transp Res Part Transp Environ 2024;134:104343. https://doi.org/10.1016/j.trd.2024.104343.
[52] Zhang Q, Yin J, Fang T, Guo Q, Sun J, Peng J, et al. Regenerative braking system effectively reduces the formation of brake wear particles. J Hazard Mater 2024;465:133350. https://doi.org/10.1016/j.jhazmat.2023.133350.