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Quantitative modeling of China's commercial vehicle powertrain transition toward 2050: Market penetration, uncertainty, and policy impacts

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ABSTRACT

China's commercial vehicle (CV) sector, including heavy-, medium-, and light-duty trucks and city buses, accounts for 54.1% of CO_2 emissions from road transportation, highlighting its significant role in the national broader efforts to manage emissions. This study develops the Sustainability Outlook for Commercial Vehicles (SOC) model, a quantitative framework projecting powertrain transitions in China's CV market through 2050. The model simulates fleet agents, evaluates perceived cost of ownership (PCO), and incorporates market fluctuations using Monte Carlo methods. It assesses five powertrains — diesel (DV), natural gas (NGV), battery electric (BEV), plug-in hybrid (PHEV), and fuel cell electric (FCEV) — across four CV categories, considering regional variations in energy prices, usage, and infrastructure. Results show continued BEV growth by 2050, with city buses reaching 98% electrification and BEV shares of 34% in HDTs and 22% in LDTs. DVs retain over 30% market share in 2050. NGVs peak near 50% in 2030 due to low gas prices but later decline, remaining competitive mainly in northern and northwestern regions. PHEVs play niche roles, and FCEVs face limited adoption due to the high cost of hydrogen and utilization uncertainties. Battery-swapping BEVs offer PCO advantages for vehicle lifespans under 11 years, while plug-in charging BEVs dominate longer-term use as the swapping advantage narrows. Short-term purchase subsidies for HDTs deliver greater carbon-reduction benefits — on average, 5.05 times those of long-term policy scenarios — though they do not significantly shift long-term transition pace. The study provides a comprehensive roadmap to support China's transition to sustainable CVs.

1. Introduction

Commercial vehicles (CVs), comprising various categories of trucks and buses, form the backbone of China's logistics and passenger transport systems, playing a critical role in facilitating the transition of the transport sector toward sustainability. Despite accounting for less than 15% of total vehicle sales and stock in China [1,2], CVs remain indispensable to economic circulation, undertaking 73.6% of the national freight volume and nearly 18% of passenger traffic [3]. However, their crucial economic role is accompanied by substantial environmental challenges. Distinct operational characteristics, such as significantly higher annual vehicle kilometers traveled (AVKT) compared to passenger vehicles (PVs), drive fuel-intensive usage patterns. A higher AVKT for CVs results in higher fuel consumption than that for PVs. The AVKT of heavy-duty trucks (HDTs) exceeds 50,000 km, while that of light-duty trucks (LDTs) exceeds 20,000 km, both more than double that of PVs [4]. Consequently, CVs consumed 227 million tons of diesel in 2020, accounting for 53.2% of energy consumption [5,6]. They also accounted for 54.1% of road carbon emissions in 2024 [7]. Against the backdrop of China's ambitious dual-carbon goal [8], the Chinese government has prioritized reducing carbon emissions from CVs to address their substantial environmental impact [9]. These facts underscore the importance of CVs' sustainable powertrain transition in the process of carbon reduction.

Incentive policies have been widely adopted by governments worldwide to promote the sustainable transition of CVs [10], including tax credits [11], purchase subsidies [12], and infrastructure-related

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Nomenclature

AVKT	Annual Vehicle Kilometers Traveled	BAU	Business-as-usual
BEV	Battery Electric Vehicle	Charge-BEV	Plug-in Charging Battery Electric Vehicle
CI	Confidence Interval	China-SAE	China Society of Automotive Engineers
CNG	Compressed Natural Gas	CNY	Chinese Yuan
CV	Commercial Vehicle	DGE	Diesel Gallon Equivalent, an energy unit
DOE	U.S. Department of Energy	DV	Diesel Vehicle
E.U.	European Union	EIA	U.S. Energy Information Administration
FCEV	Fuel Cell Electric Vehicle	GCW	Gross Combination Weight (Maximum Mass)
GHG	Greenhouse Gas	GVWR	Gross Vehicle Weight Rating
HDP	High Diesel Price	HDT	Heavy-duty Truck
HEP	High Electricity Price	HHA	High Hydrogen Station Accessibility
HHP	High Hydrogen Price	ICEV	Internal Combustion Engine Vehicle
IEA	International Energy Agency	kWh	Kilowatt-hour, an energy unit
LCA	Life Cycle Assessment	LDP	Low Diesel Price
LDT	Light-duty Truck	LEP	Low Electricity Price
LHA-1	Low Hydrogen Station Accessibility Level-1	LHA-2	Low Hydrogen Station Accessibility Level-2
LHP	Low Hydrogen Price	LNG	Liquefied Natural Gas
lb	A weight unit, 1 lb≈0.4536 kg	MCS	The Monte Carlo Simulation
MDT	Medium-duty Truck	MS	Market Share
MSRP	Manufacturer's Suggested Retail Price	NEV	New Energy Vehicle
NGV	Natural Gas Vehicle	PCO	Perceived Cost of Ownership
PEV	Plug-in Electric Vehicle	PHEV	Plug-in Hybrid Electric Vehicle
PV	Passenger Vehicle	RMSE	Root-Mean-Square Error
SHA	Stagnant Hydrogen Station Accessibility	SOC	Sustainability Outlook for Commercial Vehicles
Swap-BEV	Battery-Swapping Battery Electric Vehicle	t	Ton, a weight unit, 1 ton = 1,000 kg
TCO	Total Cost of Ownership	UF	Utility Factor (for PHEV)
U.S.	United States	USD	United States Dollar
VKT	Vehicle Kilometers Traveled	WTW	Well-to-Wheel

incentives [13]. The subsidy levels for sustainable CVs in Europe are highly uneven. One-third of European Union (E.U.) member states do not provide any purchase incentives for sustainable CVs [14]. Most countries offer purchase incentives ranging from 20% to 40%, with the highest reaching USD 465,040 in Malta [15]. In the United States (U.S.), tax credits for sustainable CVs can reach up to USD 40,000 [16]. In Japan, beyond the base subsidy of up to USD 4900 [17], an additional hydrogen fuel subsidy of USD 4.80 per kg is provided for fuel cell electric vehicles (FCEVs) [18]. This aligns with the target set by Japan's Ministry of Economy, Trade and Industry for FCEVs to reach over 10% penetration among HDTs by 2030 [18].

Among these measures, China's purchase subsidy policies have been shown to effectively stimulate demand for plug-in electric vehicles (PEVs) [19]. While extensive research has examined the role of subsidies in the PV market, limited attention has been paid to their effects on CVs. For example, Shang et al. [20] quantified the positive correlation between purchase subsidies and PEV adoption rates, whereas Massiani [21] analyzed the cost-effectiveness of PEV policies in Germany. Shepherd et al. [22] demonstrated that the effectiveness of subsidies largely depends on policy scenarios and assumptions about technological progress. Moreover, Guo et al. [23] argued that subsidies could generate significant economic growth but emphasized that their eventual phase-out is inevitable. In line with this, the Chinese government has announced a gradual phase-out plan for subsidies and tax exemptions [24]. However, the policy trajectory for CV purchase subsidies and their phase-out remains uncertain, especially regarding their effectiveness in the sustainable transition and their carbon-reduction benefits.

The evaluation of CV powertrain technology and its economic viability has been a subject of extensive research in the academic literature. Most existing market forecasts provide deterministic estimates, effectively projecting a single fixed value for future adoption. Researchers focused on future path modeling and projections across different scenarios, offering perspectives on various factors. Lee and Thomas [25] evaluated the economic viability of electric trucks in the U.S. market using a simplified parametric life cycle assessment (LCA), providing early insights into the sustainable transition of medium-duty trucks (MDTs). Andrew et al. [26] extended the study to U.S. passenger and commercial vehicles to provide a long-term TCO analysis through 2050. It incorporates a comprehensive perspective on powertrain technologies, including internal combustion engine vehicles (ICEVs), plug-in hybrid electric vehicles (PHEVs), FCEVs, and battery electric vehicles (BEVs). Rout et al. [27] discussed the total cost of ownership (TCO) for CVs in the UK market, particularly for FCEVs and vehicle lifespan. Furthermore, Schwab et al. [28] quantified the impacts of BEVs on the power grid and incorporated these effects into their analysis of market penetration and charging strategies.

China has a large market size for sustainable CVs, with the world's largest total volume [29,30] and a unique policy landscape [31]. Researchers in China have primarily focused on TCO assessments and short- to medium-term evaluations of emerging powertrain technologies in the national market. Mao et al. [32] analyzed the TCO of HDTs, but their projection horizon was limited to 2021–2030 and excluded natural gas vehicles (NGVs). Hao et al. [33] introduced the concept of Perceived Cost of Ownership (PCO), highlighting the role of implicit costs and demonstrating the economic potential of NGVs. Yet, their work did not extend to exploring future market dynamics. Similarly, Feng and Dong [34] investigated how sustainable powertrain designs and battery degradation models affect LDTs, although they did not consider longer-term market dynamics. Zhao et al. [35] emphasized comparing BEVs and diesel vehicles (DVs), examining usage patterns, technological characteristics, and charging infrastructure, and supported their findings with empirical data from real-world operations. More recently, Xue et al. [36] combined LCA, TCO analysis, and engineering simulation to assess HDTs in China through 2035. However, despite the comprehensive framework of this research, it still falls short in capturing long-term market evolution.

Table 1
Overview of studies on CV cost analysis and projections.

Authors	Research subject	Technology type	Research scope	Methodology	Time span	Contributions	Limits
Lee and Thomas [25]	MDT	DV/NGV/BEV	U.S.	Simplified parametric LCA	Instant	Early-stage economic assessment of electric trucks	Lacks future market projections
Andrew et al. [26]	PVs and CVs	ICEV/BEV/PHEV/FCEV	U.S.	TCO analysis	2020–2050	Comprehensive LCA and long-term TCO forecast to 2050	Lacks analysis of city buses, geographical limitations
Hao et al. [33]	CVs	DV/NGV/BEV/FCEV	China	PCO analysis	Instant	Highlights NGV's current economic advantages, considers implicit costs	Lacks future market projections
Schwab et al. [28]	PVs	ICEV/BEV	Germany	TCO analysis, adapted GATE electricity model	2035	Considers PEV impact on the electricity sector	Limited TCO indicators, lacks implicit cost evaluation
Rout et al. [27]	HDT	DV/BEV/FCEV	UK and E.U.	TCO analysis	2021–2050	Detailed FCEV cost analysis, favorable TCO scenarios for FCEV	Lacks quantification of implicit costs
Feng and Dong [34]	LDT	ICEV/BEV/PHEV/FCEV	China	TCO analysis, powertrain, and battery models	2023	Considers the prospects of LDT technologies	Lacks future projections
Pasaoglu et al. [43]	PVs	ICEV/BEV/PHEV/FCEV	E.U.	System dynamics simulation and agent-based model	2010–2050	A comprehensive representation of the light-duty vehicle fleet evolution in Europe	Lacks quantification of implicit cost and market uncertainty
Xue et al. [36]	HDT	ICEV/BEV/FCEV	China	LCA, TCO analysis, engineering simulation	2035	Uses powertrain models to analyze HDT energy use and life-cycle economics	Lacks continuous projections, no NGV focus

Battery-Swapping BEVs (Swap-BEVs) have attracted significant attention in China [37], as they are perceived to mitigate range anxiety [38] and to enhance transportation efficiency [39]. Existing research has primarily focused on specific vehicle segments. For instance, Yang et al. [40] conducted an LCA including Swap-BEVs and concluded that LDTs and MDTs currently show no cost advantage. Wu et al. [41] found that for HDTs, Swap-BEVs exhibit better cost-effectiveness than DVs over their full life cycle, despite being less economically competitive than plug-in charging BEVs (Charge-BEVs) at present. Furthermore, Zhu et al. [39] compared two BEV modes under varying conditions of battery-swapping station utilization, vehicle operating speed, and charging distance. They suggested that with future advancements in battery technology, the geographical suitability of battery swapping is likely to expand. This effect may be further enhanced in areas with higher traffic density. Although Swap-BEVs are widely regarded as a promising powertrain technology for HDTs [42], few studies have incorporated Swap-BEVs into market modeling frameworks.

In summary, a review of the extant literature is provided in Table 1. However, uncertainty modeling in the CV market is a salient topic for discussion, as it is imprudent to assign definitive values to potential future development scenarios. Moreover, many studies often fail to conduct refined modeling across representative regions of China, despite the significant differences in energy infrastructure, energy prices, and policies. The impacts of policy subsidies for CVs are often not adequately analyzed. Finally, Swap-BEV has been a neglected subject in extant market modeling studies, even though it makes a significant contribution to the current HDT market, accounting for approximately 40% of BEVs [44].

To address existing research gaps, this study develops a projection framework for the long-term, sustainable transition of the CV market. The research focuses on four vehicle types and six powertrain technologies across four representative regions, providing a comprehensive yet bounded system perspective. To realistically capture market heterogeneity, a Monte Carlo Simulation (MCS) approach is employed to generate fleet agents that reflect real-world characteristics and to assess the uncertainty ranges of different powertrain technologies under multiple confidence levels. Building on these elements, the study introduces the Sustainability Outlook for Commercial Vehicles (SOC) model. To capture implicit costs not reflected in TCO, the SOC framework adopts a PCO formulation and integrates it with Monte Carlo–based uncertainty analysis. The model projects market-driven powertrain adoption trajectories under exogenous assumptions about technology attributes, infrastructure availability, energy prices, business strategies, and policy incentives. The principal contributions of this study are summarized as follows:

- **Comprehensive and long-term research scope:** This study covers the four main types of CVs (HDT, MDT, LDT, City bus) and five powertrain technologies (DV, NGV, BEV, PHEV, FCEV), encompassing nearly all CV powertrain technologies in the Chinese market. The SOC model provides market dynamics projections up to 2050, considering both national and regional perspectives to explore developmental deviations across representative regions with different energy resources and infrastructure. In particular, the SOC model evaluates future adoption trends for BEVs under two modes: Swap-BEV and Charge-BEV.

- **Agent-based market projection (macro level):** An agent-based framework is introduced in which statistically representative fleet agents are generated via Monte Carlo sampling and aggregated to market outcomes by segment and region. Unlike many prior agent-based models that focus on micro-level behavioral choices, this design links agent heterogeneity (e.g., vehicle kilometers traveled, VKT) to market-level penetration trajectories through a transparent PCO-based decision rule with calibrated implicit costs, thereby enabling macro projections under limited data.
- **Explicit uncertainty quantification:** Stochastic input vectors (usage, costs, and technical parameters) are propagated through the non-linear PCO–choice mapping to yield empirical confidence bands (median, interquartile range, and 99.3% intervals) for technology shares. This goes beyond single-point or deterministic projections and complements traditional discrete-choice or logit formulations by providing direct, model-based uncertainty intervals for market penetration.
- **Scenario-based analysis of energy, infrastructure, and policy effects:** This study uses systematic scenario design to evaluate the market impacts of energy prices, infrastructure accessibility, and subsidy policies. The study quantifies the carbon-reduction benefits of different subsidy policies.

The remainder of this study is organized as follows: Section 2 introduces the source and processing method of the data; Section 3 explains the principles of the methodology and the specific structure of the model; Section 4 presents the market penetration projections of various powertrain technologies, discusses the prospects of the two electricity replenishment modes of BEV and the applicable operation, designs a series of scenarios to quantify different cost factors, and optimizes the subsidy policies for maximum carbon-reduction benefit; finally, Section 5 summarizes the contributions and policy recommendations of this study and outlines the future research directions.

2. Data

2.1. Data indicators and their division

The SOC model focuses on four types of CVs: HDT, MDT, LDT, and City Bus. It considers five powertrain technologies, including DV, NGV, BEV, PHEV, and FCEV. NGVs refer to internal combustion engine vehicles that use liquefied natural gas (LNG) or compressed natural gas (CNG) as fuel. The research subjects of this study are illustrated in Fig. 1. Table 2 summarizes a series of mainstream classification standards based on weight.

The model inputs include fleet agent parameters, detailed in PCO calculation parameters. The PCO parameters, spanning a temporal scope up to 2050, are classified into deterministic and uncertain data across three domains: vehicle, infrastructure, and policy parameters. The detailed sources are shown in Table 3 and Appendix A.

2.2. Data processing

Accessibility of refueling stations. The accessibility of refueling stations is measured using a dimensionless variable ranging from 0 to 1. It reflects the implicit costs of the refueling process. Location data for all refueling stations, including diesel, natural gas, hydrogen, and charging stations, is collected from the open data platform provided by Amap, the most commonly used navigation app in China, by February 2025 [51]. Subsequently, an MCS is employed to randomly generate 200,000 sample points across China's primary highway network, including provincial highways and above. A one-to-one mapping is established by pairing each road sample point with its nearest refueling station. The average time to reach a refueling station is derived from actual navigation times calculated by Amap [51], as shown in the online simulation results in Fig. 2(a) and (b). The simulation minimizes the inclusion of data collected during periods of traffic congestion.

This analysis defines accessibility based on the varying levels of development across Chinese provinces. The relationship between accessibility and refueling time is modeled using an exponential fit, as shown in Fig. 2(c) and Eq. (11). The accessibility of natural gas refueling stations is assumed to remain constant. In regions characterized by mature natural gas refueling infrastructure, such as North China, the accessibility already exceeds 0.8. This level implies that the corresponding refueling time is under 36 min, rendering range anxiety negligible. For charging stations, simulations indicate minimal differences in accessibility compared to diesel stations. Furthermore, the accessibility of hydrogen stations is projected to reach the current level of natural gas stations by 2050. Consequently, station accessibility is used to quantify the implicit costs in PCO, particularly for sustainable technology powertrains.

Uncertain input data. The SOC model simulates fleet agents and vehicle technological characteristics using a set of uncertain inputs drawn from specified probability distributions. The distribution parameters are informed by existing literature and fitted using publicly available data. Detailed descriptions of the data sources and parameter settings are provided in Appendix A.

3. Model methodology

3.1. Monte Carlo simulation of fleets

The SOC model utilizes a fleet-agent algorithm based on PCO minimization by MCS [52]. Fleet agents are generated using key operational parameters: VKT (X_i), lifespan (l_i), discount rate (d_i), and refueling penalty costs (η_i). Crucially, these parameters are treated as stochastic rather than static point estimates, enabling the generation of heterogeneous fleet agents even with limited data in the CV market.

As illustrated in Fig. 3, the algorithm generates a distinct set of fleet agents tailored to each specific vehicle type (e.g., HDT, MDT, LDT, and city bus). In each Monte Carlo iteration, a random parameter vector θ_i is sampled for every agent, as given in Eq. (1). Each agent then selects the powertrain option with the lowest generalized cost, and the aggregation of these decisions yields the market adoption probabilities.

$$\begin{cases} \theta_i = \{X_i, l_i, d_i, \eta_i\}, \\ X_i \sim \text{Gamma}(\alpha_x, \beta_x) \\ d_i \sim Normal(\alpha_d, \beta_d) \\ \eta_i \sim Lognorm(\alpha_\eta, \beta_\eta) \end{cases} \tag{1}$$

3.2. Calculation of PCO

The PCO incorporates five cost components, as shown in Eq. (2).

$$T_{i,j} = T_{i,j}^{\text{purchase}} + T_{i,j}^{\text{fuel}} + T_{i,j}^{\text{inconvenience}} + T_{i,j}^{\text{maintain}} + T_{i,j}^{\text{other}} \tag{2}$$

Where, i represents a member of the vehicle type set {HDT, MDT, LDT, City Bus}, and j denotes a member of the powertrain technology set {DV, NGV, BEV, PHEV, FCEV}. $T_{i,j}^{\text{purchase}}$ denotes the vehicle purchase cost. $T_{i,j}^{\text{fuel}}$ refers to the fuel cost. $T_{i,j}^{\text{inconvenience}}$ captures the implicit cost associated with the inconvenience of a given energy-replenishment method. $T_{i,j}^{\text{maintain}}$ represents life-cycle costs such as maintenance, repairs, insurance, and tolls. $T_{i,j}^{\text{other}}$ covers additional unquantified costs, calibrated using historical market data.

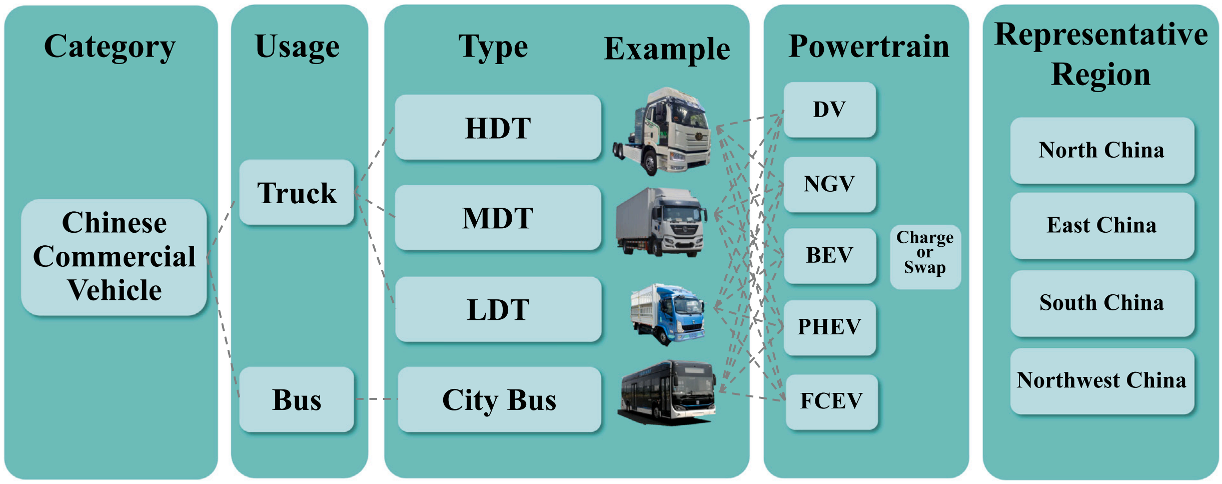

Fig. 1. Analysis framework of SOC model.

Table 2
Vehicle classification comparison among China, the U.S., and the E.U.

Type	China	U.S.	E.U.
HDT	GCW ≥ 12 t Heavy Trailer: GCW ≥ 12 t	Class 8: GVWR ≥ 33,000 lb Class 7: 26,000 < GVWR ≤ 33,000 lb	N3: GCW ≥ 12 t O4: max mass ≥ 10 t
MDT	4.5 t ≤ GCW < 12 t	Class 6: 19,500 < GVWR ≤ 26,000 lb Class 5: 16,000 < GVWR ≤ 19,500 lb Class 4: 14,000 < GVWR ≤ 16,000 lb Class 3: 10,000 < GVWR ≤ 14,000 lb	N2: 3.5 t ≤ GCW < 12 t
LDT	3.5 t <GCW < 4.5 t	Class 2: 6000 < GVWR ≤ 10,000 lb Class 1: GVWR ≤ 6000 lb	N1: GCW < 3.5 t
Bus	Large: Length ≥ 6 m or Seats ≥ 20 Medium: Length < 6 m or Seats 10–19 Small: Length < 6 m or Seats ≤ 9	Light-duty: GVWR < 8500 lb Medium-duty: 8501 < GVWR ≤ 10,000 lb Heavy-duty: GVWR > 10,000 lb	M3: Seats > 8, mass > 5 t M2: Seats > 8, mass ≤ 5 t M1: Seats ≤ 8, no standing space
Sources	[45,46]	[47]	[48]

Notes: (1) GCW = Gross Combination Weight (Maximum Mass), GVWR = Gross Vehicle Weight Rating.
(2) Trucks with a weight of less than 3.5 t are called mini trucks and are not discussed in this study.

Table 3
Model input indicators and definitions.

Parameter category	Indicator	Definition	Unit
Vehicle Parameters	Vehicle Price (uncertain input data)	The purchase cost of the vehicle for consumers.	USD
	Insurance Cost	The annual insurance cost of the vehicle.	USD
	Toll Cost	The toll cost per kilometer for the vehicle.	USD/km
	Maintenance Cost	The vehicle's maintenance cost per kilometer	USD/km
	Energy Consumption Rate (uncertain input data)	The amount of energy consumed by the vehicle per kilometer.	DGE/km
	Driving Range (BEV, PHEV & FCEV) (uncertain input data)	The maximum distance a vehicle can travel on a single energy charge or fuel cell refill.	km
	Idling Energy Consumption Rate	The energy consumption rate in an idle state.	DGE/hour
Infrastructure Parameters	Accessibility of Refueling Stations	Quantifies the extent and accessibility of refueling or recharging facilities for each powertrain type.	0-1 variable
	Charging Power (BEV&PHEV)	The average charging power provided by charging stations for BEVs.	kW
	Fuel Prices	The cost of fuel (e.g., diesel, electricity, hydrogen, LNG/CNG) required for vehicle operation.	USD/DGE
Policy Parameters	Purchase Subsidy Incentives	Financial incentives are provided to promote vehicle purchases.	0-1 variable

Notes: (1) Inflation effects are not considered; the exchange rate [49] is based on 2023 conversion: 1 USD = 7.075 CNY.
(2) DGE (Diesel Gallon Equivalent) is an energy unit commonly used by the U.S. Department of Energy, representing the energy content of one gallon of diesel. Energy equivalency conversions for different fuels are based on the United States Department of Energy [50].

Purchase cost. The vehicle purchase prices are defined in Eqs. (3) and (4). For DV and NGV, the purchase cost is set to the average manufacturer's suggested retail price (MSRP). For new energy vehicles (NEVs, including BEVs, PHEVs, and FCEVs), the MSRP is multiplied by an incentive coefficient, γ_{NEV}, to reflect subsidy policies. The MSRP projections are based on a component-level cost breakdown, with detailed information provided in Appendix A.

$$T_{i,j}^{\text{purchase}} = \mathrm{MSRP}_j^i, j = \{\mathrm{DV}, \mathrm{NGV}\} \tag{3}$$

$$T_{i,j}^{\text{purchase}} = \mathrm{MSRP}_j^i \cdot (1 - \gamma_{\mathrm{NEV}}), j = \{\mathrm{BEV}, \mathrm{PHEV}, \mathrm{FCEV}\} \tag{4}$$

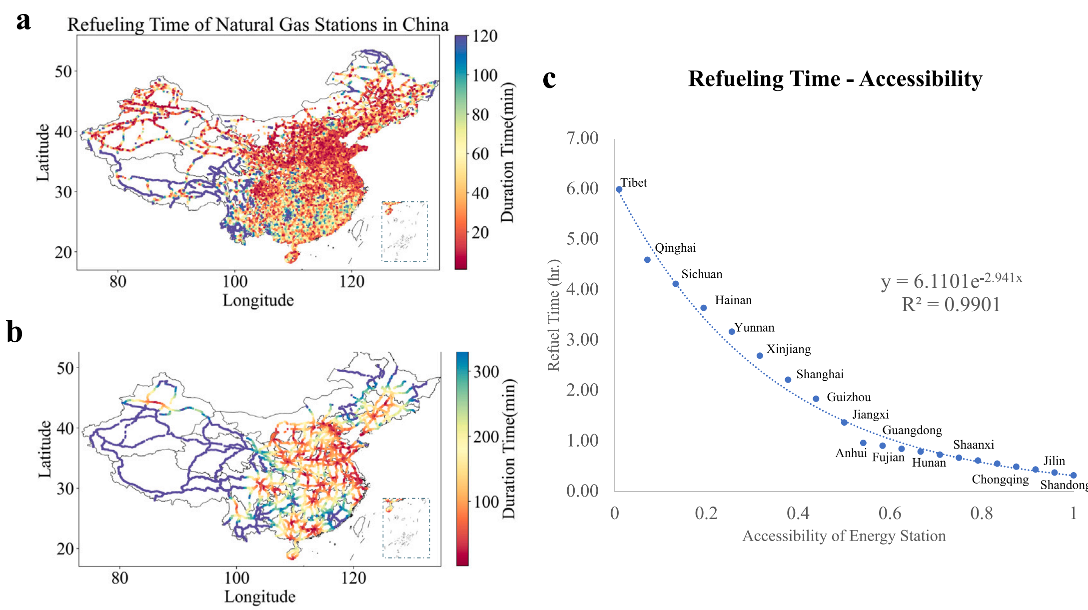

Fig. 2. Quantification of the accessibility of refueling stations.

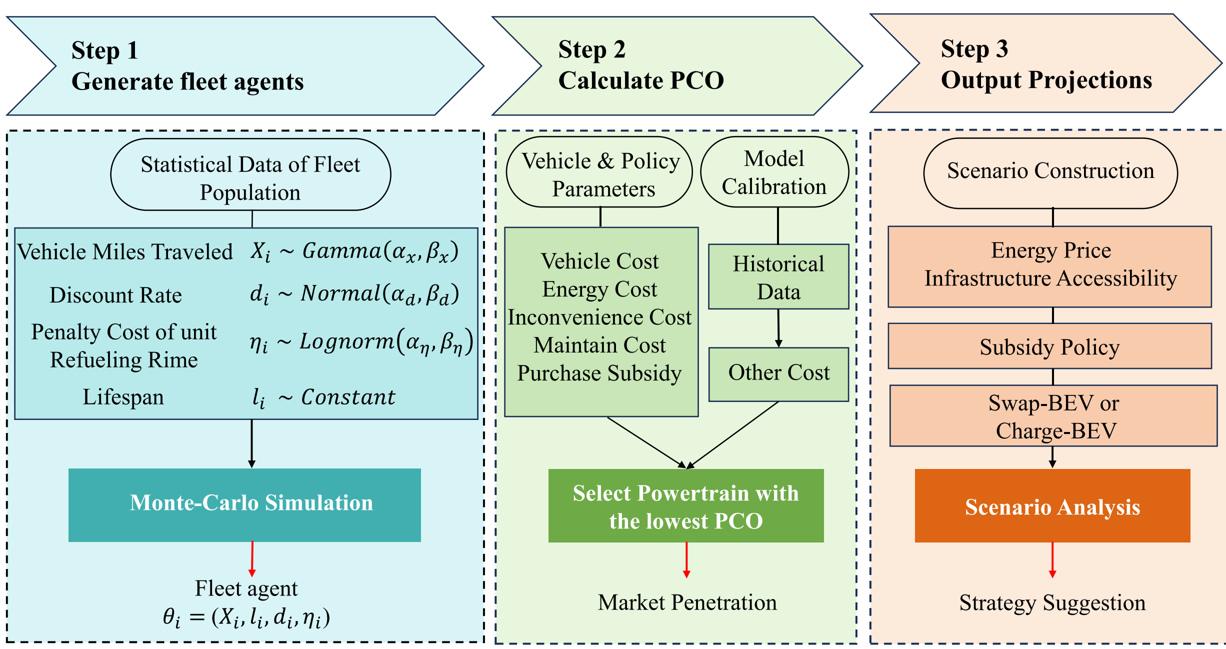

Fig. 3. Workflow of the SOC model.

Maintenance costs. The maintenance cost $C_{i,j}^{\text{maintain}}$, which includes vehicle insurance premiums, routine maintenance expenses, and toll fees, is projected using fixed values [53].

$$C_{i,j}^{\text{maintain}} = C_{i,j}^{\text{insurance}} + X_i \cdot (C_{i,j}^{\text{toll}} + C_{i,j}^{\text{maintenance}}) \tag{5}$$

Fuel cost. The fuel cost $T_{i,j}^{\text{fuel}}$ is composed of the on-road fuel cost $T_{i,j}^{\text{on-road fuel}}$ and the idle fuel cost $T_{i,j}^{\text{idlefuel}}$, as given in Eqs. (6) and (7).

$$T_{i,j}^{\text{fuel}} = T_{i,j}^{\text{on-road fuel}} + T_{i,j}^{\text{idlefuel}} \tag{6}$$

$$T_{i,j}^{\text{on-road fuel}} = l_i \cdot c_{i,j}^{\text{fuel}} \cdot X_i \cdot P_j, j \neq \text{PHEV} \tag{7}$$

$$\begin{aligned} T_{i,j}^{\text{on-road fuel}} = l_i \cdot \{ & c_j^{\text{electricity}} \cdot (X_i \cdot \text{UF}) \cdot P_{\text{electricity}} \\ & + c_{i,j}^{\text{diesel}} \cdot [X_i \cdot (1 - \text{UF})] \cdot P_{\text{diesel}} \}, j = \text{PHEV} \end{aligned} \tag{8}$$

$$T_{i,j}^{\text{idlefuel}} = l_i \cdot f_{i,j}^{\text{idle}} \cdot h_i^{\text{idle}} \cdot P_j, j = \{\text{DV, NGV}\} \tag{9}$$

In Eq. (7), l_i refers to the vehicle lifespan, $c_{i,j}$ refers to the energy consumption per kilometer, and P_j is the price of fuel for j. For PHEVs, a utility factor (UF) of 0.523 is applied to LDTs to simulate real-world electricity consumption [54], whereas a UF of 0.25 is applied to MDTs and HDTs [55]. $T_{i,j}^{\text{on-road fuel}}$ is calculated accordingly using Eq. (8). The idling fuel cost $T_{i,j}^{\text{idlefuel}} \neq 0$, if $i = \text{HDT}, j = \{\text{DV, NGV}\}$. It is related to the idling fuel consumption rate $f_{i,j}^{\text{idle}}$ and the annual idling time h_i^{idle} of the vehicle, as shown in Eq. (9). Based on the assumption that the deterioration of fuel economy with engine age is negligible; Eq. (7) adopts a linear relationship between mileage and fuel cost [56].

Inconvenience cost. The simulation of the refueling time for diesel stations (t_{diesel}) in China is conducted in Section 2.2, and the time is determined to follow a Lognormal distribution with parameters $Lognormal(0, 0.17173)$. The refueling time of FCEV and NGV is given in Eq. (10):

$$\begin{cases} t_{i,j}^{\text{relative}} = \varphi(\alpha_j) - t_{\text{diesel}} & \varphi(\alpha_j) > t_{\text{diesel}} \\ t_{i,j}^{\text{relative}} = 0 & \varphi(\alpha_j) \le t_{\text{diesel}} \end{cases} \tag{10}$$

$$\varphi(\alpha_j) = 6.1101 \exp(-2.941\alpha_j) \tag{11}$$

$\varphi(\alpha_j)$ is related to the accessibility of the refueling station α_j in Eq. (11), as illustrated in Fig. 2(c). $r_{i,j}$ represents the driving range, and χ is set to 140, corresponding to the annual refueling frequency of NGVs. The time penalty coefficient η_i is set at three times the average driver's wage [57], expressed in dollars per hour. The inconvenience cost $T_{i,j}^{\text{inconvenience}}$ of these two powertrain technologies is defined as shown in Eq. (12):

$$\begin{cases} T_{i,j}^{\text{inconvenience}} = l_i \cdot (\frac{X_i}{r_{i,j}} \cdot t_{i,j}^{\text{relative}}) \cdot \eta_i, j = \text{FCEV} \\ T_{i,j}^{\text{inconvenience}} = l_i \cdot (\chi \cdot t_{i,j}^{\text{relative}}) \cdot \eta_i, j = \text{NGV} \end{cases} \tag{12}$$

As shown in Eq. (13), $t_{i,j}^{\text{charge}}$ is related to the annual electricity consumption value and the charging power p_j^{charge} in Eq. (14). The initial State of Charge is set to 20%, following the values adopted by Kostopoulos et al. [58] and Wang et al. [59], that is, $\theta = 0.8$. Additionally, in a real-world scenario, PHEV owners are unlikely to reduce their working hours solely for charging, leading to $T_{i,\text{PHEV}}^{\text{inconvenience}} = 0$.

$$T_{i,j}^{\text{inconvenience}} = l_i \cdot t_{i,j}^{\text{charge}} \cdot \eta_i, j = \text{BEV} \tag{13}$$

$$t_{i,j}^{\text{charge}} = \frac{c_{i,j}^{\text{fuel}} \cdot X_i}{p_j^{\text{charge}}}, j = \text{BEV} \tag{14}$$

The Agents compare the $T_{i,j}$ values of vehicles with different powertrain technologies and select the option with the lowest $T_{i,j}$, as shown in Eq. (15). Aggregating these choices across all agents yields the market shares of each powertrain type, calculated using Eq. (16).

$$v^* = \arg \min_{j \in \{\text{DV, NGV, BEV, PHEV, FCEV}\}} PCO_j \tag{15}$$

$$MS_j = \frac{N_j}{N_{\text{total}}} \tag{16}$$

3.3. Model calibration

Model calibration is essential for aligning historical data with real market trends and improving the accuracy of projections. $T_{i,j}^{\text{other}}$ captures factors that are difficult to quantify but still influence vehicle choices, such as potential policy shifts, technological uncertainties, and behavioral biases.

The primary objective of calibration is to minimize the error between the projected market shares of various powertrain technologies and the actual market shares by adjusting $T_{i,j}^{\text{other}}$. Eq. (17) is adopted to measure the difference between the projected values and the true values.

$$\text{Min(Error)} = \sum_{t=2018}^{2024} \sqrt{\sum_{j \in \{\text{BEV, PHEV, FCEV, NGV}\}} (M_{j,t}^{\text{pre}} - M_{j,t}^{\text{tru}})^2} \tag{17}$$

Where, $M_{j,t}^{\text{pre}}$ and $M_{j,t}^{\text{tru}}$ represent the projected and actual market shares of powertrain technology j in the year t. The calibration process adopts an optimization algorithm to iteratively adjust $T_{i,j}^{\text{other}}$

Table 4
The annual average RMSE between the projected value and the real value.

Vehicle type	Powertrain	Average annual RMSE
HDT	DV	0.018
	NGV	0.012
	BEV	0.011
	PHEV	0.012
	FCEV	0.012
MDT	DV	0.009
	NGV	0.002
	BEV	0.005
	PHEV	0.002
	FCEV	0.005
LDT	DV	0.014
	NGV	0.004
	BEV	0.008
	PHEV	0.005
	FCEV	0.008
City Bus	DV	0.017
	NGV	0.004
	BEV	0.016
	PHEV	0.007
	FCEV	0.010

The model outputs align with the historical statistics reported by the China Association of Automobile Manufacturers (CAAM) [60]. The calibration yields annual root-mean-square errors (RMSEs) ranging from 0.002 to 0.018, indicating strong agreement with historical data, as summarized in Table 4. Since 20 vehicle models are involved, the statistical boxplots of the errors and their RMSE values are provided in the Appendix A Figures S5–S7 (a)–(t) to verify the model's excellent validity.

Although the calibrated term $T_{i,j}^{\text{other}}$ is introduced to ensure consistency between modeled outcomes and historical market observations, it does not represent a purely arbitrary fitting parameter. Instead, it aggregates economically meaningful but unobserved influences on fleet purchase decisions, such as preferences for specific vehicle models or features, heterogeneous risk attitudes, operational considerations, and policy or institutional effects that are not explicitly quantified in the model.

Due to the lack of detailed survey-based or micro-level behavioral data, these effects cannot be separately identified and are therefore treated as a calibrated average within each segment and powertrain. While this approach improves historical consistency, it may limit the model's ability to capture future structural shifts in preferences or policy regimes, which should be addressed in future work as richer data become available.

3.4. Quantification of PCO for BEV operating business modes

Two BEV recharging modes are considered: Charge-BEV and Swap-BEV. The Swap-BEV is a BEV designed to swap its depleted battery for a fully charged one at a battery-swapping station. This mode allows the entire energy replenishment process to typically take less than 5 min [42]. The Charge-BEV refers to a BEV that recharges exclusively at charging stations. The SOC model focuses on regions where swapping-station availability is adequate, and the relative PCO model is adjusted to distinguish between the two BEV modes.

$$\begin{aligned} \text{PCO}_{Relative} = & T^{\text{purchase}}(\text{purchase price, battery lease price}) + \\ & T^{\text{inconvenience}}(\text{charging time, swapping time}) + \\ & T^{\text{fuel}}(\text{electricity fee}, \text{Price}_{\text{service}}) \end{aligned} \tag{18}$$

$\text{PCO}_{Relative}$ is simplified into three components, as shown in Eq. (18): the purchase cost T^{purchase}, the inconvenience cost $T^{\text{inconvenience}}$, and the fuel cost T^{fuel}. The model incorporates the cost associated with a potential new battery replacement for Charge-BEVs, as defined in

Eq. (19). $\tau_{\text{new battery replacement}}$ is the threshold of VKT for new battery replacement. As shown in Eq. (20), the purchase price of Swap-BEV, $T^{\text{purchase}}_{\text{Swap-BEV}}$, consists of the base purchase price $\text{Price}_{\text{base}}$ and the battery lease price $\text{Price}_{\text{battery lease}}$. $\text{Price}_{\text{battery lease}}$ represents the annual battery lease cost, determined by the terms of the leasing contract. The inconvenience cost of Charge-BEV is the same as Eq. (13). For Swap-BEVs, the inconvenience cost $T^{\text{inconvenience}}_{\text{Charge-BEV}}$ depends on the constant battery-swapping time η, which replaces the charging time in Eq. (21).

$$\begin{cases} T^{\text{purchase}}_{\text{Charge-BEV}} = \text{Price}_{\text{base}} + \delta \cdot \text{Price}_{\text{new battery}}, \delta \in \{0,1\} \\ \delta = 0, \text{if } X_i < \tau_{\text{new battery replacement}} \\ \delta = 1, \text{if } X_i \geq \tau_{\text{new battery replacement}} \end{cases} \tag{19}$$

$$T^{\text{purchase}}_{\text{Swap-BEV}} = \text{Price}_{\text{base}} + \text{Price}_{\text{battery lease}} \cdot l_i \tag{20}$$

$$\begin{cases} T^{\text{inconvenience}}_{\text{Swap-BEV}} = l_i \cdot \eta_i \cdot \frac{X_i}{r_{i,j} \cdot \theta} \\ T^{\text{inconvenience}}_{\text{Charge-BEV}} = l_i \cdot t^{\text{refuel}}_{\text{Charge-BEV}} \end{cases} \tag{21}$$

The fuel cost of Charge-BEV is consistent with Eq. (6). The battery-swapping service contract generally stipulates that the electricity fee for Swap-BEV is waived within a certain value κ (see Table S3). If the annual electricity consumption value K is higher than κ, an additional service fee must be paid, as specified in Eq. (22). In addition, since 72.5% of China's HDTs do not operate under fleet management, the model does not account for cost differences arising from fleet size [61]. The model estimates the probability that an HDT fleet agent chooses Charge-BEV over Swap-BEV as a function of vehicle lifespan.

$$\begin{cases} T^{\text{fuel}}_{\text{Swap-BEV}} = \text{Price}_{\text{service}} \\ K = l_i \cdot c^{\text{electricity}}_{i,j} \cdot X_i \\ \text{Price}_{\text{service}} = 0, & K \leq \kappa \\ \text{Price}_{\text{service}} = (K - \kappa) \cdot P_{\text{electricity}}, & K > \kappa \end{cases} \tag{22}$$

3.5. Quantification method for the purchase subsidy policy impact

3.5.1. Quantifying carbon-reduction benefits

Although the SOC model is primarily designed to project the adoption of sustainable powertrain technologies, it is also utilized to evaluate subsidy policies by examining how these policies influence the technology transition. The subsidy scenario is defined by the pair (Y, γ). Here, γ, defined in Eq. (4), represents the subsidy rate in 2025, ranging from 0.05 to 0.20. Y represents the terminal year of subsidy, ranging from 2030 to 2040. The scenario (Y, γ) implies that the subsidy rate will linearly decrease from the initial rate γ in 2025 to zero in year Y.

Emissions from electricity generation are included in the calculation of well-to-wheel (WTW) greenhouse gas (GHG) emissions for BEVs. Several studies have been conducted to determine the carbon footprint of electricity, aiming to identify the carbon emission factors associated with electricity [62–64]. Emission factors for other energy sources are obtained from existing studies [65–67].

For any scenario (Y, γ) and year $t \in \{2025, \ldots, 2050\}$, the relative emission reductions and subsidy levels are defined by Eq. (23) to standardize GHG calculations. $GHG^{re}_{Y,\gamma,t}$ and $\text{Subsidy}^{re}_{Y,\gamma,t}$ may be positive or negative values, defined as shown in Eq. (24). $\text{Benefit}^{GHG}_{Y,\gamma,t}$ represents how much relative GHG decreased per USD in year t.

$$\begin{cases} GHG^{re}_{Y,\gamma,t} = GHG_{2030,0.05,t} - GHG_{Y,\gamma,t} \\ \text{Subsidy}^{re}_{Y,\gamma,t} = \text{Subsidy}_{Y,\gamma,t} - \text{Subsidy}_{2030,0.05,t} \end{cases} \tag{23}$$

$$\text{Benefit}^{GHG}_{Y,\gamma,t} := \frac{GHG^{re}_{Y,\gamma,t}}{\text{Subsidy}^{re}_{Y,\gamma,t}}, \quad \text{unit: t } CO_2/\text{USD}. \tag{24}$$

For each scenario, the following conditions in any year (2025–2050) are calculated in Eq. (25).

$$\begin{cases} \text{Benefit}^{GHG}_{Y,\gamma,t} > 0, & \text{if } GHG^{re}_{Y,\gamma,t} > 0, \text{Subsidy}^{re}_{Y,\gamma,t} > 0 \\ \text{Benefit}^{GHG}_{Y,\gamma,t} < 0, & \text{if } GHG^{re}_{Y,\gamma,t} < 0, \text{Subsidy}^{re}_{Y,\gamma,t} > 0 \end{cases} \tag{25}$$

As shown in Eq. (26), $\overline{\text{Benefit}^{GHG}_{Y,\gamma}}$ represents the average benefit relative to the minimum subsidy scenario. It is transformed to $\widetilde{\text{Benefit}}^{GHG}_{Y,\gamma}$ using Eq. (27), with (2030, 10%) taken as the reference case for convenience. A larger $\widetilde{\text{Benefit}}^{GHG}_{Y,\gamma}$ indicates a greater benefit from carbon reduction.

$$\overline{\text{Benefit}^{GHG}_{Y,\gamma}} = \sum_{t \in \{2025,\ldots,2050\} \cap \{\text{Subsidy}^{re}_{Y,\gamma,t} \neq 0\}} \text{Benefit}^{GHG}_{Y,\gamma,t} \Big/ (t - 2025 + 1). \tag{26}$$

$$\widetilde{\text{Benefit}}^{GHG}_{Y,\gamma} = \overline{\text{Benefit}^{GHG}_{Y,\gamma}} - \overline{\text{Benefit}^{GHG}_{2030,10\%}} \tag{27}$$

Because these outcomes involve uncertainty and assess only the vehicle-use phase, the values represent relative benefits and are meaningful only within the same category. Despite this inherent uncertainty, statistical tests confirm the model's robustness, with a normalized RMSE of 0.05 or less.

3.5.2. Quantifying rebound effects

The analysis adopts the classical definition of the rebound effect proposed by Berkhout et al. [68]. It is defined as the regression of the market share of sustainable technologies under subsidy policy scenarios, as shown in Eq. (28).

$$\text{Rebound Effect}_t(Y,\gamma) := MS^{sustainable}_t(Y,\gamma) - MS^{sustainable}_{t+1}(Y,\gamma), \tag{28}$$

where the condition

$$MS^{sustainable}_t(Y,\gamma) > MS^{sustainable}_{t+1}(Y,\gamma)$$

must hold.

For each policy scenario, the total rebound effect over the analysis period is defined as:

$$\text{Rebound Effect}_{total}(Y,\gamma) := \sum_{t=2025}^{2050} \text{Rebound Effect}_t(Y,\gamma), \tag{29}$$

and the average rebound effect is given by:

$$\text{Rebound Effect}_{average}(Y,\gamma) := \frac{\text{Rebound Effect}_{total}(Y,\gamma)}{\text{Number}\left\{t \mid \text{Rebound Effect}_t(Y,\gamma) > 0\right\}}. \tag{30}$$

As shown in Eq. (30), $\text{Number}\{\cdot\}$ denotes the cardinality of the set of years in which the rebound effect is positive.

4. Result analysis and discussions

4.1. Powertrain transition pathways toward 2050

4.1.1. Business-as-usual evolution of powertrain in China

Under the Business-as-Usual (BAU) scenario, the SOC model simulates a range of powertrain adoption outcomes using MCS. Figs. 4 and 5 present the resulting box-and-whisker plots, which project the development of China's CV powertrains and show the uncertainty ranges (50%–99.3% confidence). The analysis reveals both common patterns and sharply diverging trends across vehicle types, with HDTs showing the most dynamic technological shift at the national level. Key assumptions for the BAU scenario are as follows: diesel prices are projected using the method of Ou et al. [69], with the values fluctuating between 4.19 and 4.41 USD/gal; electricity is priced stably at 1.00 CNY/kWh; hydrogen prices decline linearly to 6.00 USD/kg by 2050; hydrogen refueling accessibility reaches parity with the current natural-gas station network by 2050; and the purchase subsidy is 10% in 2025, phasing out linearly to 0% by 2035.

Heavy-duty Truck: As shown in Fig. 4(a), DVs are projected to retain a significant presence — over 30% by 2050 — due to their

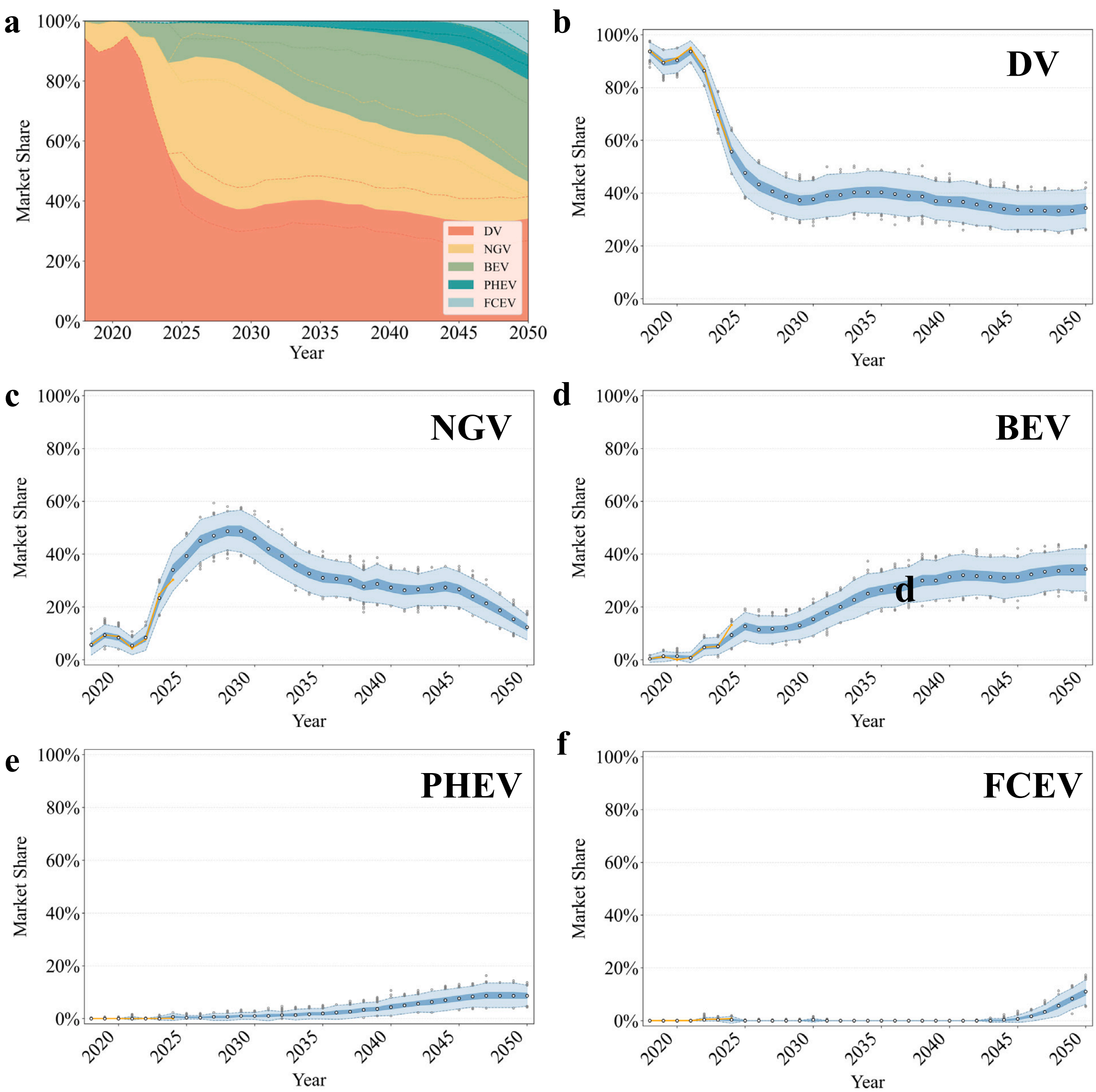

Fig. 4. Market share projection of HDT in 2018–2050.
Notes: **(a)** represents the overall HDT market forecast. The area within the dashed lines of the same color indicates the interval range under a 99.3% probability, which also corresponds to the outer dashed lines of different powertrain technologies as **(b)**, **(c)**, **(d)**, **(e)**, and **(f)**. The orange solid line is labeled as real historical data for reference. **The two ranges correspond to the projected 50% (dark blue) and 99.3%** ($\pm 3\sigma$, **light blue) probability levels.** Data points located outside the whiskers are considered outliers, which are attributed to rare simulation anomalies.

proven durability, cost-effectiveness, and established refueling infrastructure. However, this represents a substantial decline from the 70%+ dominance observed in 2025, signaling an ongoing erosion of DV market share.

NGVs, supported by mature refueling networks and low fuel prices after 2023, are expected to reach nearly 50% penetration by 2030, as shown in Fig. 4(c). This transitional surge is short-lived, as their cost advantage declines after 2030, and market share is projected to fall to 12.3% by 2050.

BEVs emerge as a steadily growing sustainable technology. Following a moderate rise through 2030, driven by limited driving ranges and high vehicle costs, the BEV share climbs steadily to 34% by 2050, with an upper uncertainty bound exceeding 42%, as shown in Fig. 4(d). In the national BAU scenario, this trajectory positions BEVs as the prominent sustainable powertrain technology by mid-century, contrasting sharply with today's NGV domination.

PHEVs, serving as a transitional solution by mitigating range anxiety, gain traction post-2030. Despite slow early growth, their market share reaches 8.7% by 2050, as shown in Fig. 4(e), aided by cost reductions and improved utility factors.

FCEVs, despite the policy backing, remain marginal. High hydrogen costs and slow infrastructure rollout are expected to limit their market share to below 5% by 2050, as shown in Fig. 4(f), even under optimistic assumptions regarding infrastructure rollout.

Medium-Duty Trucks: As shown in Fig. 5(a), MDTs exhibit the least diversification in powertrain evolution. DVs continue to dominate due to their payload efficiency and market maturity. BEVs remain negligible until 2030, limited by battery weight and range, but increase to 24.1% by 2050 as vehicle costs decline. Other alternatives — NGVs,

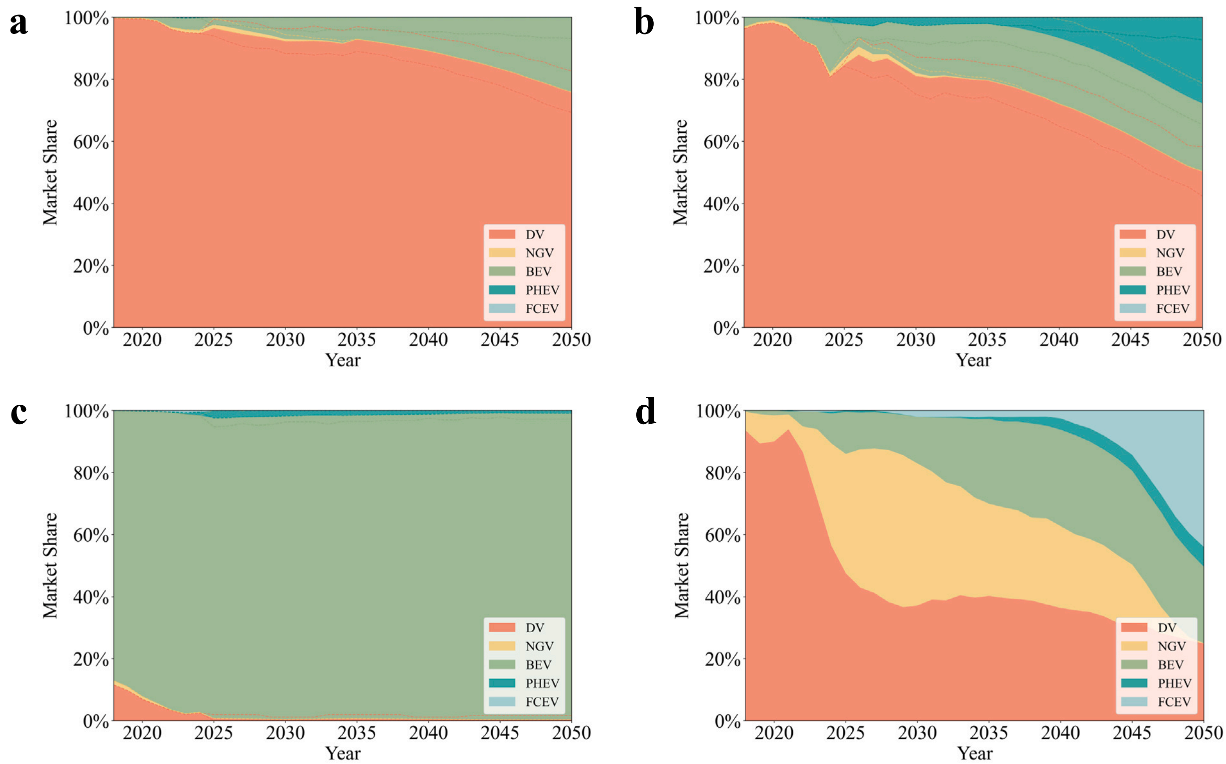

Fig. 5. Market share projections for other CV types and HDT in the LHP (low hydrogen price) scenario.
Notes: **(a)**, **(b)**, and **(c)** are the market share forecasts for MDT, LDT, and City Bus. Detailed figures similar to Fig. 4 are listed in Appendix A. **(d)** shows the results of the sensitivity analysis under the low hydrogen price assumption (4 USD/kg in 2050) for HDT..

FCEVs, and PHEVs — struggle to compete due to payload penalties, high vehicle costs, or limited utility factors.

Light-Duty Trucks: Fig. 5(b) illustrates a more competitive landscape for LDTs. BEVs, benefiting from lower "inconvenience costs" and urban suitability, reach 15.3% by 2030 and 21.8% by 2050. PHEVs show the most pronounced growth among all vehicle types, rising to 27.8% by 2050, driven by declining upfront costs, long driving range, and high fuel economy. This positions PHEVs as a key technology in the LDT segment, in contrast to their limited influence in the HDT and MDT markets.

City Buses: Over the past five years, China's city bus fleet has undergone a significant electrification, with the share of BEVs reaching 95.66% in 2024 [70]. As purchase costs continue to decline, BEVs will further displace DVs. PHEVs may have carved out a niche in longer urban routes, striking a balance between fuel cost savings and emission requirements. As Fig. 5(c) illustrates, excluding BEVs, other powertrain technologies lack either competitive cost or infrastructure support.

In contrast to 2024, when NGVs dominate the HDT market, the BAU scenario points toward a long-term transition to BEVs and PHEVs, particularly in HDT and LDT applications. NGVs serve as a short-term bridge technology, whereas FCEVs lag behind. The momentum of BEVs grows steadily after 2030, positioning them as the cornerstone of China's CV future—a transition driven by policy support, cost trends, and technological advancements.

4.1.2. Regional heterogeneity in transition dynamics

The adoption of NGVs in China exhibits substantial regional heterogeneity, primarily influenced by variations in local energy structures, infrastructure accessibility, and regional policies. This study focuses on four representative regions: North China, Northwest China, East China, and South China, as shown in Fig. 6(a). North and Northwest China are resource-abundant, together accounting for 80% of China's coal reserves and 57.7% of its natural gas reserves [71]. These regions benefit from lower natural gas prices and more developed refueling infrastructure. In contrast, East and South China face higher natural gas costs and more limited refueling infrastructure, resulting in less favorable conditions for NGV deployment. It should be noted that this study does not account for variations in fuel economy caused by road conditions or differences in charging power due to infrastructure limitations, as accurate and reliable province-level data are unavailable. Fig. 6(b)–(e) present the projected regional market shares across the four representative regions.

In North China, NGVs are projected to retain a long-term competitive advantage. As of 2023, the NGV penetration rate had already reached 47.4%, effectively displacing a significant portion of DVs. This share is expected to peak at approximately 64% in 2028, then gradually decline to stabilize around 36.3% by 2050. The significant cost advantage of NGVs in this region has been shown to hinder BEV adoption and substantially undermine FCEV competitiveness. Similarly, in Northwest China, NGVs also have a strong market presence, with a 50.8% penetration rate in 2023 and a projected 29.9% penetration rate by 2050. The relatively small difference in station accessibility between diesel and natural gas reduces the inconvenience cost of NGV usage, further contributing to their sustained adoption in this region.

East and South China exhibit markedly lower NGV market shares, currently at 15.8% and 9.0%. This can be attributed to two primary barriers: higher regional natural gas prices and underdeveloped NGV refueling infrastructure. Under these conditions, NGVs serve primarily as transitional technologies, with their market share declining more rapidly than in other regions. Interestingly, the relative density of hydrogen refueling infrastructure in East and South China has begun to reduce the inconvenience cost associated with FCEVs. As a result, these regions may offer a more conducive environment for the early deployment of FCEVs. Model projections suggest that FCEV market shares in East and South China could reach approximately 14% by 2050, indicating their growing viability in energy-scarce but economically advanced areas.

Although China has not yet established a comprehensive national plan for CV decarbonization, the Commercial Vehicle Carbon Neutrality Technology Roadmap 1.0, published by the China Society of Automotive Engineers (China-SAE) [6], anticipates FCEV penetration of 42% nationwide by 2050. Compared with regional projections, the East and South China markets are projected to fall short of this target; however, the BEV penetration gap narrows to 6%, and FCEV penetration reaches approximately 28%. These differences suggest that policies should be adapted to local energy structures and economic conditions rather than applied uniformly nationwide.

4.1.3. PCO comparison for BEV operating business modes

A critical dimension of China's CV electrification lies in evaluating the PCO performance of Charge-BEV versus Swap-BEV operating business modes for HDTs. The adoption dynamics of Charge-BEVs and Swap-BEVs are analyzed in regions with sufficient battery-swapping stations. As shown in Fig. 7, the preference probability depends on both the vehicle's operational lifespan and its deployment year.

In the scenario without new battery replacement for Charge-BEVs, Swap-BEVs exhibit a pronounced PCO advantage for short-lifespan operations (< 8 years), particularly in the early phase of the transition. In 2025, for vehicles with a 5-year lifespan, the preference probability of Swap-BEVs reaches 83.2%. Although this dominance gradually decreases, Swap-BEVs remain competitive until around 2034, when their preference probability equals that of Charge-BEVs. After 2040, Swap-BEVs sustain a stable yet reduced share of about 43.9%, reflecting the impact of shorter vehicle lifespans.

For vehicles with moderate to long lifespans (≥ 8 years), Charge-BEVs demonstrate a clear and PCO advantage over Swap-BEVs. In the 8–9 year range, the competitiveness of Swap-BEVs diminishes rapidly—by 2030, their preference probability falls to approximately 24%, and drops to below 8% after 2040. This decline is further accentuated in scenarios with a lifespan of 10 years or more, where Charge-BEVs maintain dominant PCO performance across all deployment years. The reduced PCO-effectiveness of Swap-BEVs is primarily due to the cumulative burden of battery leasing, which outweighs their initial capital and convenience benefits.

In the scenario with new battery replacement for Charge-BEVs, Swap-BEVs exhibit a better PCO advantage when the lifespan is below 11 years, as shown in Fig. 7(b). The preference probability does not vary monotonically with lifespan. In particular, for a lifespan of 7–9 years, the Swap-BEV preference probability remains above 58.0% across all deployment years. From a long-term perspective, this does not fundamentally alter the declining competitiveness of Swap-BEVs. Furthermore, the most competitive lifespan interval of Swap-BEV gradually narrows over time, decreasing from 9–12 years in 2024 to 8–9 years in 2040 due to variations introduced by battery replacement costs. Fig. 7(c) illustrates the probability differences between scenarios with and without new battery replacement for selected representative years. Consistent with the compression of the lifespan interval, the lifespan corresponding to the highest Swap-BEV preference probability shifts forward over time, from 11 years in 2025 to 8 years in 2050.

In conclusion, vehicle lifespan remains a decisive factor in determining the PCO-preferred BEV mode. When the battery replacement cost of Charge-BEVs is considered, the advantage of Swap-BEVs persists only within a limited lifespan range, mainly below 11 years. This competitive window gradually narrows over time. Although Swap-BEVs demonstrate short-term PCO efficiency, their long-term competitiveness declines as their optimal lifespan shortens. This reduction in optimal lifespan simultaneously leads to a diminished PCO advantage over time. Conversely, Charge-BEVs become increasingly viable for long-term deployment, benefiting from continued reductions in battery costs and improvements in charging infrastructure. Moving forward, refining the battery-swapping business model and optimizing lifecycle cost management are essential to the sustainable development of Swap-BEVs.

4.1.4. Scenario analysis of energy prices and infrastructure accessibility

The model quantifies the impact of key cost parameters to identify the sensitive factors that influence the sustainable transition of CV, providing targeted recommendations for potential market and policy interventions. A series of market scenarios is developed in addition to the BAU, as shown in Table 5.

The sensitivity to energy price variations. To assess the sensitivity of different powertrain technologies to fluctuations in fuel prices, six energy price scenarios are developed, considering variations in diesel, electricity, and hydrogen prices (Figs. 8 and 9), including High Diesel Price (HDP), Low Diesel Price (LDP), High Electricity Price (HEP), Low Electricity Price (LEP), High Hydrogen Price (HHP), and Low Hydrogen Price (LHP). The specific definitions for all scenarios are detailed in Table 5. The projected market shares for the four HDT powertrain technologies, as well as for MDT-DVs and City Bus-BEVs, are shown in Fig. 9(a)–(f).

Diesel prices can significantly influence the process of sustainable powertrain technologies. The penetration rate of DV is highly sensitive to diesel prices, and its development in the HDP scenario is restricted. DV market share in HDTs drops to between 0.7% and 6.0% in 2030, and further to 0% and 2.7% by 2035, as shown in Fig. 8(a) and 8(b). Similar declines are observed in MDTs and LDTs, with DV shares falling by 31.5% and 51.8%, respectively. In the LDP scenario, the penetration of all sustainable powertrain technologies falls significantly below BAU levels. By 2035, the DV penetration exceeds 80% in HDTs (85.2%), MDTs (98.9%), and LDTs (95.0%), with only slight decreases by 2050—still higher than in the BAU scenario.

The HDP scenario also drives a substantial increase in NGV adoption across all truck segments. For HDTs, NGV penetration approaches 60%, driven by natural gas's relative fuel cost advantage. While other sustainable powertrain technologies benefit to a certain extent from higher diesel prices, their relative advantage is expected to diminish by 2050. These findings demonstrate that diesel prices are a pivotal factor in CV's sustainable transition. Specifically, lower diesel prices provide fleets with a limited incentive to shift away from traditional powertrain technologies.

Electricity prices do not substantially affect the sustainable transition. In even the HEP scenario, BEVs maintain a robust competitive advantage due to their superior fuel economy, particularly during the initial application period. The BEV penetration of HDTs differs little from the BAU scenario before 2030 (9.7% in 2025, 11.8% in 2030), but increases notably thereafter, reaching 16.24% in 2036. In the LEP scenario, BEV penetration reaches its maximum value, peaking at 45.7% around 2041. Furthermore, the projection shows a 99.3% probability that penetration will exceed 53.7% under this scenario, clearly highlighting the substantial potential of BEVs under favorable cost conditions.

The adoption of FCEVs for HDTs remains highly uncertain and is critically contingent on the hydrogen price. While the LHP scenario can trigger the rapid market expansion of FCEVs, their market performance in other scenarios is mediocre. Specifically, under the LHP scenario, the FCEV share grows significantly from 3% in 2039 to 42.8% in 2050, largely displacing DVs and NGVs. This suggests that the large-scale adoption of FCEVs is theoretically possible only under highly optimistic assumptions.

The impact of hydrogen station accessibility on FCEV development. This study quantifies the market impacts of hydrogen station accessibility, underscoring the critical role of such scaled infrastructure in shaping the adoption dynamics of FCEVs. Four scenarios are introduced to explore the impact of hydrogen station accessibility on FCEVs: High Hydrogen Station Accessibility (HHA, high hydrogen station accessibility scenario, where accessibility reaches parity with diesel stations by 2050), Low Hydrogen Station Accessibility 1 (LHA-1, low hydrogen station accessibility scenario (level 1), where accessibility improves to 1/2 BAU level by 2050), Low Hydrogen Station Accessibility 2 (LHA-2,

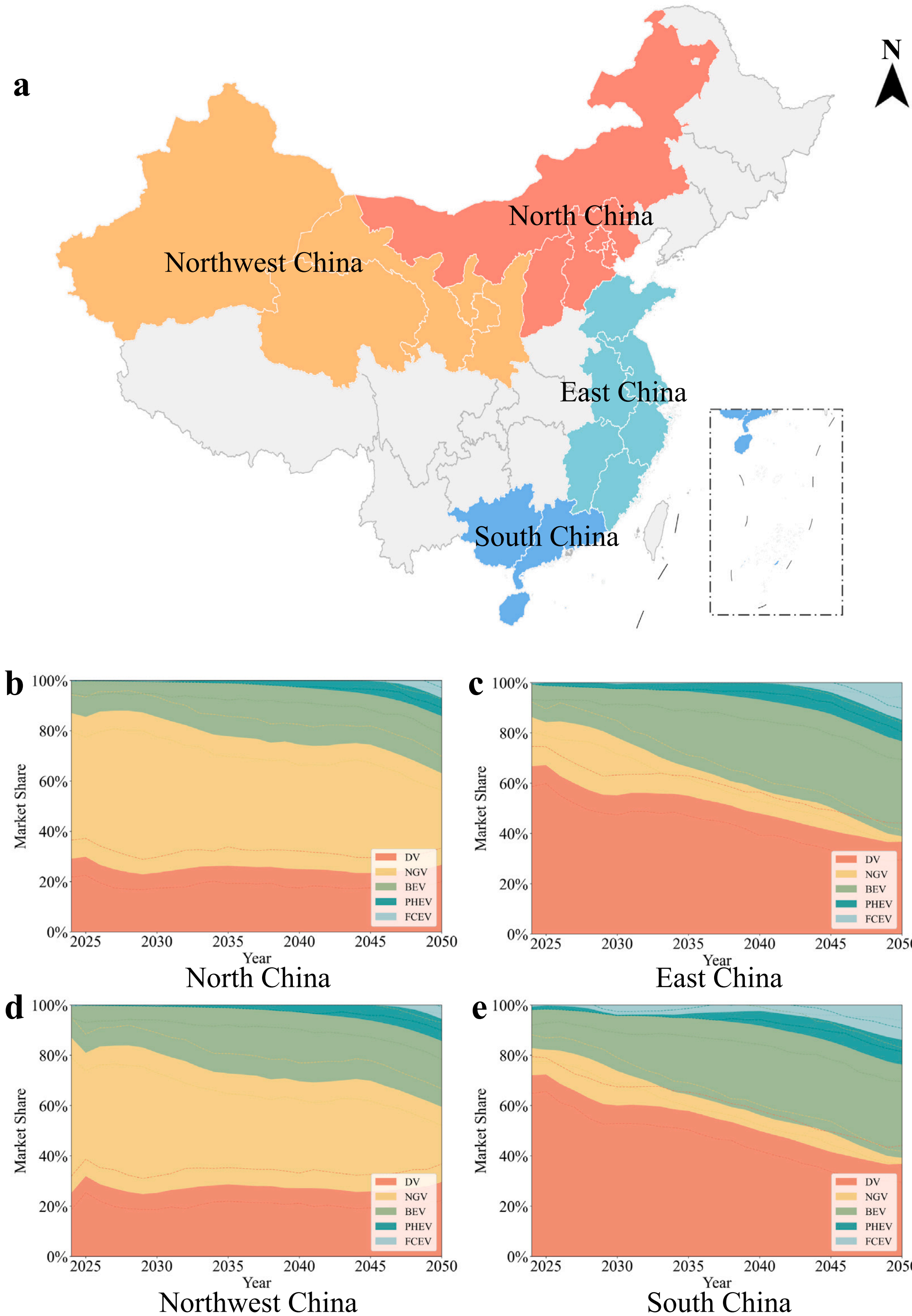

Fig. 6. Powertrain market share projections for selected representative regions in China.
Notes: **(a)** presents the geographical location map and division of the four representative regions selected for this study..

low hydrogen station accessibility scenario (level 2), where accessibility improves to 1/4 BAU level by 2050), and Stagnant Hydrogen Station Accessibility (SHA, stagnant hydrogen station accessibility scenario, where accessibility remains at the current level through 2050).

Hydrogen station accessibility is a crucial prerequisite for the scale-up of FCEVs. A minimum infrastructure threshold, though not necessarily high, is essential to support the adoption of emerging technologies. By 2050, FCEV shares fall by only 1.6% and 3.98% under LHA-1 and LHA-2, respectively, compared to the BAU, as shown in Fig. 9(d). However, under the SHA scenario, the FCEV penetration drops to just 0.25%. This contrast emphasizes that successful government promotion of sustainable powertrain technologies requires sufficient and sustained investment in the corresponding infrastructure to meet real-world operational demands.

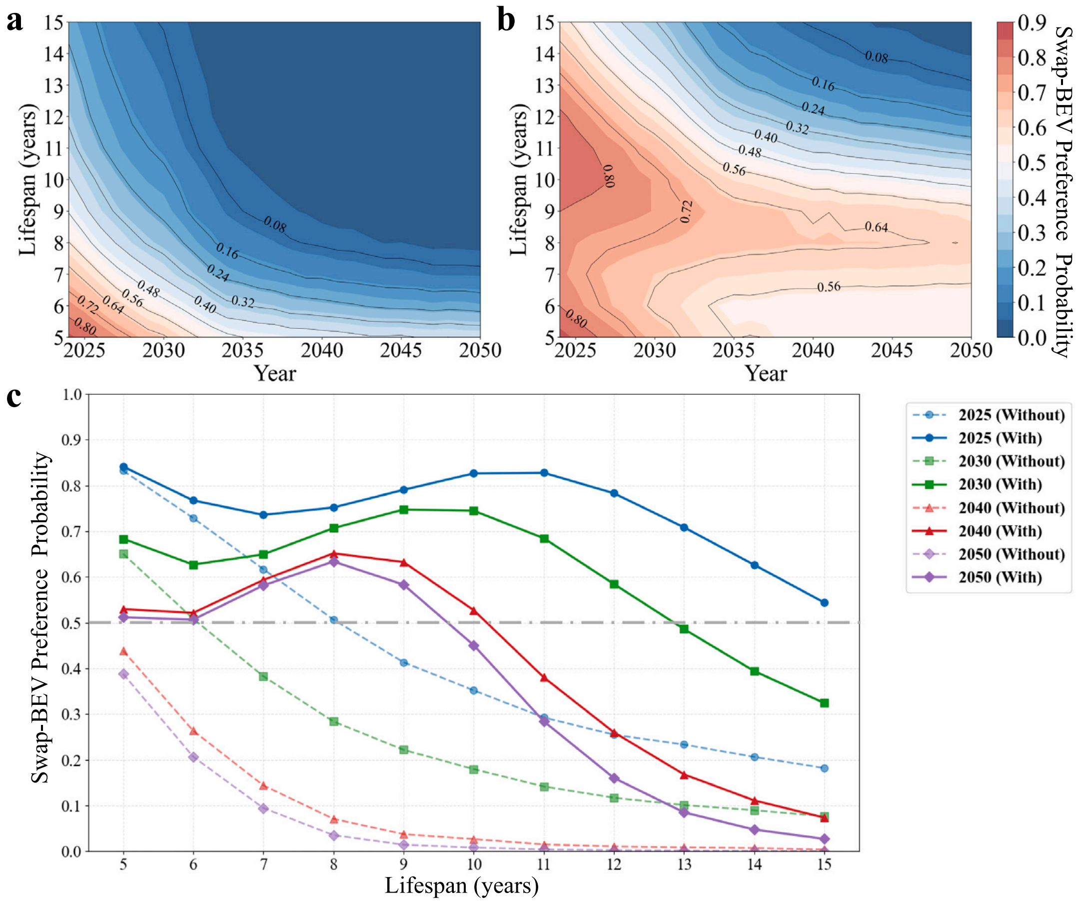

Fig. 7. The preference probability of the HDT fleet choosing Swap-BEVs.
Notes: **(a)** and **(b)** show the adoption dynamics in scenarios without and with new battery replacement for Charge-BEVs. **(c)** compares the differences between these scenarios in selected years..

Table 5
Acronyms and corresponding scenario descriptions.

Acronym	Scenario description
BAU	Business-as-usual scenario: diesel price range is 4.19-4.41 USD/gal, adopting the method of Ou et al. [69]; electricity is priced stably at 1.00 CNY/kWh; hydrogen prices decline linearly to 6.00 USD/kg by 2050 [72]; the accessibility of hydrogen refueling stations reaches parity with the current natural-gas station network by 2050; and the purchase subsidy is 10% in 2025, phasing out linearly to 0% by 2035.
HDP	The high diesel price range is 6.09-7.13 USD/gal, based on the EIA [73].
LDP	The low diesel price range is 2.82 to 3.07 USD/gal, based on the EIA [73] (specific diesel prices are listed in Appendix A).
HEP	High electricity price scenario, with a constant price of 1.2 CNY/kWh.
LEP	Low electricity price scenario, with a constant price of 0.8 CNY/kWh.
HHP	High hydrogen price scenario, where the hydrogen price remains at the current level through 2050.
LHP	Low hydrogen price scenario, where the hydrogen price declines linearly to 4.0 USD/kg by 2050 [72].
HHA	High hydrogen station accessibility scenario, where accessibility reaches parity with diesel stations by 2050.
LHA-1	Low hydrogen station accessibility scenario (level 1), where accessibility improves to 1/2 BAU level by 2050.
LHA-2	Low hydrogen station accessibility scenario (level 2), where accessibility improves to 1/4 BAU level by 2050.
SHA	Stagnant hydrogen station accessibility scenario, where accessibility remains at the current level through 2050.
Subsidy(Y,γ)	The subsidy ratio is set as γ in 2025 and decreases linearly to 0 by year Y.

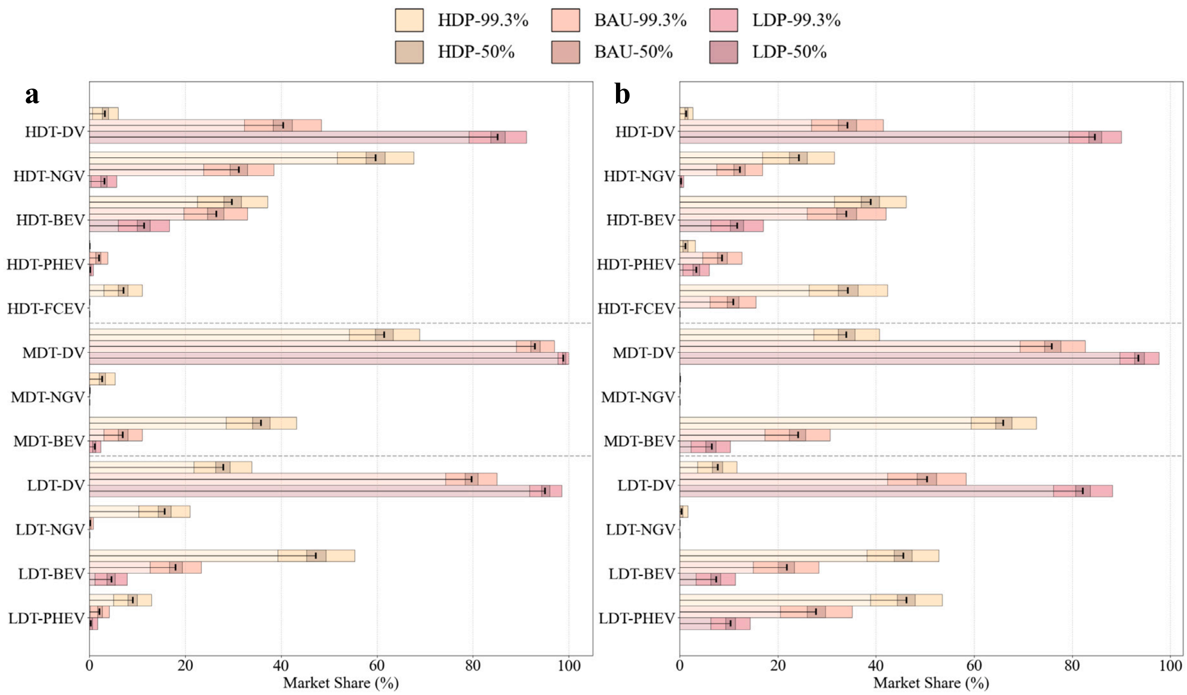

Fig. 8. Projection scenarios of diesel price in 2035 and 2050.
Notes: **(a)** represents the market reactions under the HDP and LDP scenarios in 2035, and **(b)** represents those in 2050. .

Fig. 9(e) and (f) further indicate that the market share of DV in MDTs and BEV in city buses remains high under various scenarios. In 2050, even the 99.3% lower bound in the LEP scenario still reaches 57.5%. In contrast, city buses remain predominantly electric across all scenarios, underscoring the maturity of city bus electrification in China.

4.2. Quantification of commercial vehicle subsidies for maximum carbon-reduction benefit and rebound effect

This study presents a quantitative assessment of subsidy timing and intensity, identifying cost-effective pathways and rebound effects that accelerate electrification and maximize carbon-reduction benefits. By linking fiscal support directly to decarbonization outcomes, the SOC model can provide a framework for evidence-based policy design.

For HDTs, a matrix of subsidy policy scenarios is constructed, defined by (Y, γ) in Section 3.5. The BAU scenario is specified as $(2035, 10\%)$, which is based on the current subsidy policy and the Chinese government's outlook [74]. The other policy scenarios are set according to potential policy adjustments, as detailed in Appendix A. Due to the uncertainty in model outputs, the relationship between benefits and the two policy variables is non-linear.

Subsidies are not the primary driver of the sustainable transition and have only a limited impact on accelerating it. As the SOC model incorporates the implicit cost into the PCO calculation, the proportion of purchase costs in PCO is reduced to 11%–25%, which is similar to the calculation by Hao et al. [33]. Therefore, the relative rates of sustainable transition across all scenarios remain within 3%, as shown in Fig. 10(a). Although it is generally positively correlated with both the duration and intensity of subsidies, the highest rate does not occur under the strongest subsidy scenario $(2040, 20\%)$, but instead under the scenario $(2038, 20\%)$. This outcome is driven by a rebound in DV and NGV adoptions following the complete phase-out of the strongest subsidy. These findings indicate that subsidies alone do not promote the transition at an ideal pace. Accordingly, policy design should prioritize carbon-reduction benefits rather than focus solely on accelerating the transition.

Regarding the benefits of carbon-reduction, short-term subsidy scenarios demonstrate a clear advantage. Similar to the rate of sustainable transition, the variation in carbon-reduction benefits across scenarios is limited, ranging from −8.18 to 11.22, with a normalized standard deviation of only 0.104. As shown in Fig. 10(b), the optimal benefit is observed under scenario $(2031, 5\%)$, reaching 11.22–20.03 times the average value (0.56 ± 2.02). Without distinguishing by subsidy rate, short-term subsidies ($Y < 2035$) yield significantly higher carbon-reduction benefits (1.50 ± 2.31) than long-term subsidies (Y > 2035), which average −0.37 ± 1.31. In contrast, the difference between weak ($\gamma < 13\%$) and strong ($\gamma \geq 13\%$) subsidy intensities is marginal, with average benefits of 0.74 ± 2.69 and 0.37 ± 0.94.

As shown in Fig. 10(c), significant rebound effects occur when the terminal year of the subsidy Y falls between 2030 and 2033, and the initial subsidy rate γ ranges from 17% to 20%. This critical range accounts for 44.4% of all rebound cases. The average rebound effect in this range is 1.02%, which is 21.3% higher than the overall average of 0.83%. The maximum rebound effect is found under the policy scenario $(2030, 20\%)$, where the average rebound rate reaches 1.41% and the total rebound amounts to 5.64%. These results indicate that short-term (5–8 years) and high-intensity (17%–20%) subsidies are more likely to cause noticeable rebound effects in sustainable transitions. However, the overall magnitude of these effects remains limited. It suggests that policy design should avoid short-term, high-intensity subsidies to reduce rebound effects.

The analyses of subsidy benefits and rebound effects indicate that a short-term, low-intensity subsidy is the most effective option. A 5% intensity sustained for 6 to 9 years is identified as relatively optimal. In addition, in the long term, short-term subsidies stimulate early adoption but have limited, persistent effects on market evolution. Even with varying intensities, differences in long-run outcomes remain below 3%. These findings suggest that achieving a sustainable transition requires a strategic shift in policy emphasis from direct subsidies to structural measures, such as energy-pricing reforms and robust infrastructure development, as these interventions exert a more enduring and effective impact on market transformation.

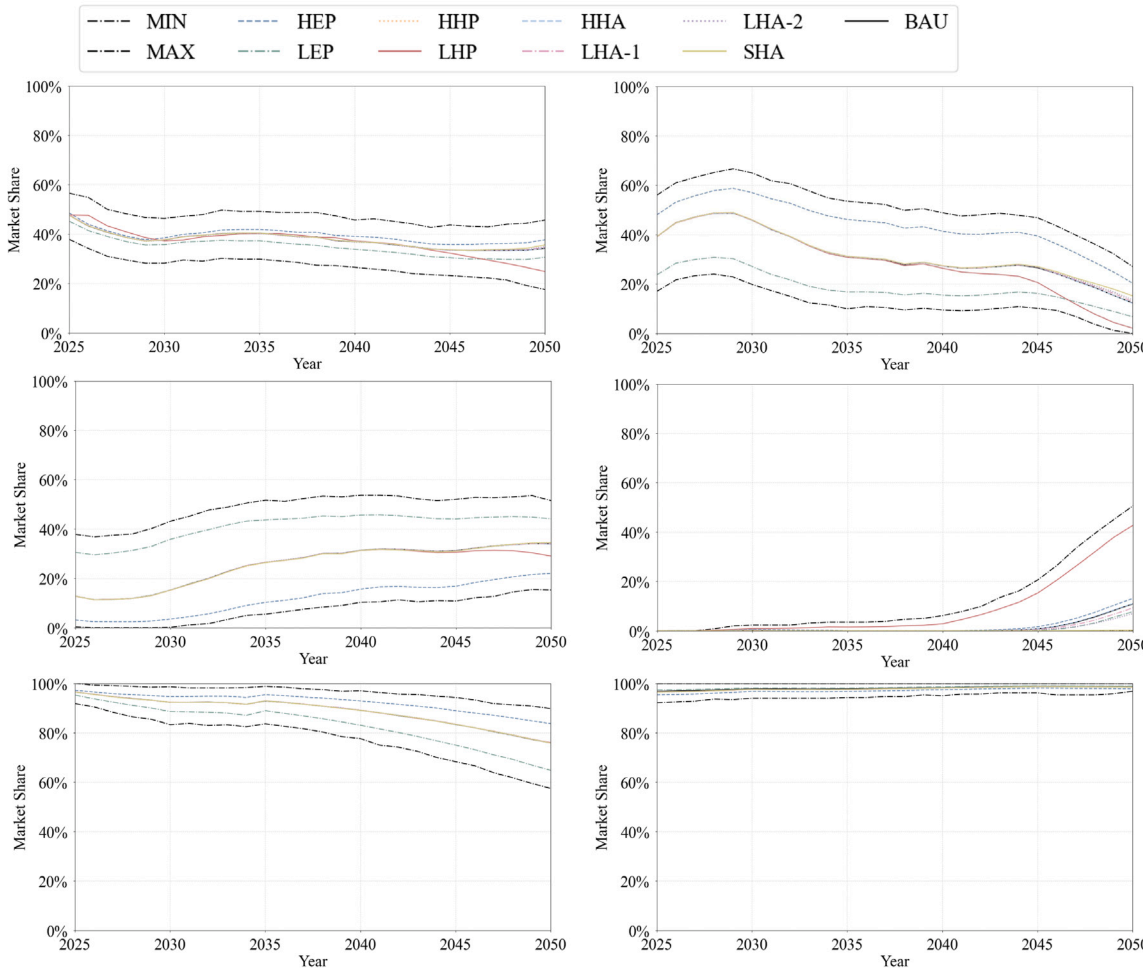

Fig. 9. Projection scenarios of renewable energy price and infrastructure accessibility.
Notes: **(a)–(f)** represent the market shares of HDT-DV, HDT-NGV, HDT-BEV, HDT-FCEV, MDT-DV, and City Bus-BEV under various scenarios. MAX/MIN is the maximum/minimum value among the 99.3% upper/lower bounds of all scenarios..

5. Conclusion

This study develops the SOC model, a market projection instrument designed to evaluate the development prospects of five major powertrain technologies across four types of CVs in China. The SOC model uses MCS to present an integrated framework for sampling fleet agents that reflect real market characteristics. It incorporates uncertain input data on driving demands and vehicle attributes. This approach enhances the precision of TCO evaluations for sustainable technologies by quantifying implicit costs. Furthermore, the model generates probabilistic projection intervals to capture market fluctuations and reflects regional heterogeneity in energy prices, vehicle specifications, and infrastructure development. A salient feature of the model is its capacity to differentiate the adoption probabilities between the two BEV operating business modes: Charge-BEVs and Swap-BEVs. Furthermore, the SOC model supports policy-relevant analyses by quantifying the impacts of alternative subsidy designs.

By using a system dynamics model to forecast potential scenarios for regions, energy, and infrastructure, in conjunction with subsidies, this study aims to provide insights into market dynamics relevant to CVs and to accelerate their sustainability. Key observations are:

- Long-term prominence of BEVs: By 2050, BEVs are projected to see continued growth, firmly establishing themselves as one of several competitive powertrain options. Excluding city buses, which are already 97% electrified by 2024, the penetration of BEVs is expected to reach 34% in HDTs and 22% in LDTs, while MDTs are expected to lag behind. Furthermore, DVs in the MDT segment demonstrate notable resilience, maintaining over 57.5% penetration even under the high diesel price scenario.
- Regional market heterogeneity: North and Northwest China's NGV market can sustain penetration rates above 30% due to favorable natural gas prices and infrastructure, while NGV adoption in East and South China is expected to decline.
- PCO comparison of BEV operating business modes: Operational lifespan decisively dictates the preference probability. Swap-BEVs exhibit a significant PCO advantage for short-term operations (< 8 years). Conversely, Charge-BEVs offer superior long-term PCO performance (≥ 8 years). Once a new battery replacement for Charge-BEVs is taken into consideration, the comparative advantage of Swap-BEVs extends to lifespans that reach 11 years. Their long-term PCO advantage then progressively weakens as this competitive window closes.
- Energy price sensitivity: Electricity and diesel prices significantly influence BEV adoption; however, BEVs still achieve over 15% penetration by 2050 under high electricity prices, demonstrating long-term economic resilience.

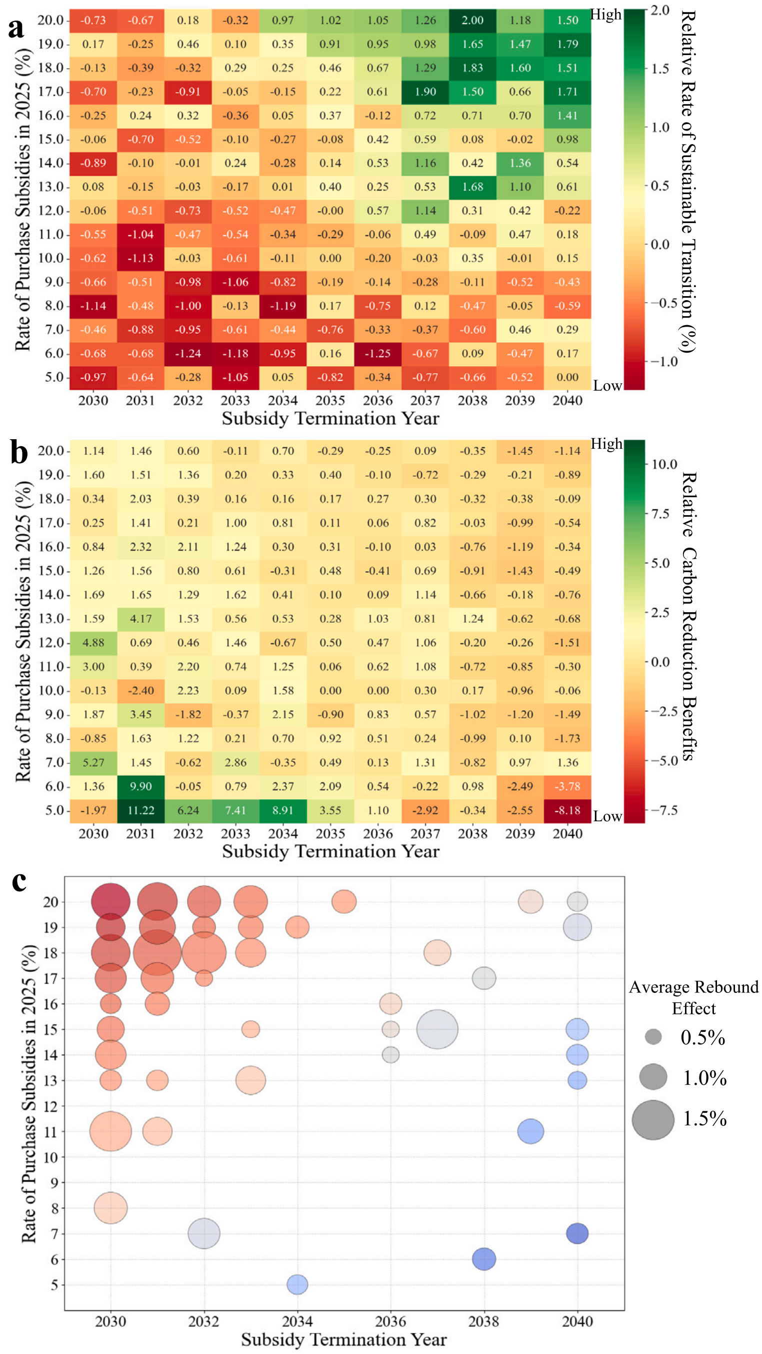

Fig. 10. Policy matrix analysis of subsidy policies.

Notes: Each grid cell represents a policy scenario (Y, γ), where the x-axis indicates the terminal year of the subsidy Y and the y-axis indicates the subsidy rate in 2025, γ. (a) represents the additional rates of sustainable transition relative to BAU $(2035, 10\%)$ as the reference, with the average relative rate across each year (2025–2050). For any scenario (Y, γ), a redder color indicates a slower transition rate, while a greener color indicates a faster transition rate. (b) represents the additional carbon-reduction benefit relative to BAU (defined as shown in Eq. (27)), i.e., the amount of carbon emissions reduced per unit of subsidy. A redder color indicates a relatively lower subsidy benefit, while a greener color indicates a relatively higher subsidy benefit..

- FCEV development and infrastructure scale: The accessibility of hydrogen refueling stations is crucial. By 2050, FCEV penetration in HDT is projected to be 0.25% under stagnant infrastructure, 6.98% with small-scale deployment, and up to 10.96% with large-scale infrastructure expansion.
- Policy effectiveness: Differences in subsidy intensity have a limited influence on the HDT transition speed, with relative penetration rate gaps remaining below 3%. Short-term subsidies yield 5.05 times greater carbon-reduction benefits than long-term subsidies, although the subsidy term shows a minimal effect. The policy rebound effect primarily occurs in scenarios with short-term (5–9 years) and high-intensity (17%–20%) subsidies. Based on these findings, this study recommends implementing a purchase subsidy policy with an intensity of 5% and a termination period between 2031 and 2034.

The SOC model shows that powertrain technologies differ in suitability across CV types. This diversity indicates that a one-size-fits-all policy approach is insufficient. Governments and industry associations need to design balanced, targeted incentives that account for vehicle costs, supporting infrastructure, energy pricing, and regional energy conditions. The findings suggest that infrastructure scaling is crucial for supporting sustainable technologies, particularly for vehicle types constrained by refueling station accessibility. Automakers should adopt region-specific technology strategies aligned with local energy markets, while battery-swapping providers should develop new operation modes to address rising lease costs driven by extended battery ranges. Short-term purchase subsidies for HDTs, coupled with a carefully planned phase-out strategy, offer the greatest potential to maximize carbon-reduction benefits. In the long term, policy efforts should strategically shift from relying on direct market subsidies to guiding the energy transition through structural reforms—specifically, energy pricing adjustments and infrastructure development.

The SOC model has not yet been used to prescribe a quantified carbon-reduction pathway and has limited precision in quantifying direct emissions. Moreover, policy instruments are treated exogenously, and economy-wide feedback, grid-capacity expansion, and supply-chain constraints are outside the scope of the present study. Furthermore, the model is restricted in addressing behavioral and infrastructure issues. The infrastructure projection assumes that hydrogen station accessibility will reach the current level of natural gas stations by 2050, without accounting for the fiscal pressures associated with large-scale hydrogen station construction. The regional differences in fuel economy caused by variations in road conditions (e.g., terrain undulations) and differences in BEV charging power resulting from disparities in charging infrastructure development levels are not explicitly quantified in the current model.

Future work will extend the framework to market-level modeling of vehicle sales, stocks, carbon emissions, and energy demand across powertrain technologies, to identify key leverage points in the CV transition toward carbon peaking and neutrality in China and globally. A comprehensive set of operational scenarios will be evaluated to determine segment-appropriate powertrain options. The resulting insights are expected to inform both technological innovation and evidence-based policy design for a more sustainable CV transition.

CRediT authorship contribution statement

Luyang Han: Writing – review & editing, Writing – original draft, Visualization, Validation, Formal analysis, Conceptualization. **Shiqi(Shawn) Ou:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization. **Luo Chen:** Resources, Methodology, Formal analysis, Conceptualization. **Ziming Yan:** Supervision, Resources, Methodology, Data curation. **Yi Zhou:** Methodology, Data curation. **Xin He:** Supervision, Resources. **Tianduo Peng:** Writing – review & editing. **Vivek T. Seshan:** Writing – review & editing. **Daniel J. De Castro Gomez:** Writing – review & editing.

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.

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Appendix A. Supplementary data

The table Data_availability.xlsx presents the data used in this study, including vehicle prices, fuel prices, energy consumption rates, and driving ranges.

Supplementary information is provided in the attachment Supplementary_information.pdf, including information on data and methodology.

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.energy.2025.139785.

Data availability

All available data are included in the Supplementary Material. An online platform presenting the model results developed in this study is publicly available at: https://soc.translab.top/.

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