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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

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Abstract: As the growing deployment towards transportation electrification, a critical focus has emerged on quantifying the reduction contribution of greenhouse gas emissions from electric vehicles towards achieving carbon neutrality under diverse policy scenarios in the future. This necessitates a dynamic model that captures the evolving composition of the vehicle fleet and accurately forecasts the penetration and developmental trajectory of the electric vehicles in the car market. However, previous studies have largely overlooked the heterogeneity in user usage attributes, rendering them less effective in evaluating the impact of usage-based incentives on electric vehicle market penetration. To bridge this research gap, this study introduces an innovative, data-driven framework that integrates system dynamics and agent-based model. The proposed model can predict levels of electric vehicle penetration and corresponding greenhouse gas emission reductions within the private passenger vehicle sector, under a variety of policy scenarios. Our findings indicate that usage-based incentives, when implemented with optimal intensity, yield more significant emission reduction impacts and long-term economic benefits compared to conventional purchase-based subsidy. These insights not only furnish actionable policy suggestions to expedite the electric vehicle industry's growth in China but also offer valuable implications for other countries seeking to implement effective strategies for combating climate change and fostering sustainable transportation initiatives.

Keywords: Electric vehicles, GHG emission, System dynamics, Agent-based model, Usage-based incentives

1. Introduction

To alleviate climate change and reduce greenhouse gas (GHG) emissions, countries around the world signed the Paris Climate Agreement in 2015. Considering China's total GHG emissions currently rank first in the world [1], China officially announced its "dual carbon" goals of reaching peak CO2 emissions before 2030 and carbon neutrality by 2060 [2]. Specifically, China's total GHG emissions from road transportation account for about 86% of the total transportation GHG emissions. GHG emission reduction in the automotive industry is an important sector of achieving the "dual carbon" goals, and therefore China has been promoting electric vehicles (EVs) strongly in the past decades. Along with the EV penetration rate boosted to higher than 20%, China has phased out the EV purchase subsidy while the tax exemption will be extended to 2025, which means the EV industry has reached a point that the market competition becomes the main driving force other than the incentives [3-5].

However, EVs are still not as cost competitive as those of equivalent internal combustion engine vehicles (ICEVs) in terms of the average retail price. Therefore, EV incentives tailored for the use phase will support the EV industry to offset the price gap in years to come. Specific policy measures such as orderly charging (OC), vehicle-to-grid (V2G), personal carbon trading (PCT), and battery recycling for electric mobility have the potential to facilitate EV diffusion. In this case, the impact of these incentivization on reducing the long-term cost of EVs' ownership deserves attention, since it is vital to maintain a high penetration rate of EVs towards the transportation sector's carbon neutrality. Consequently, a dynamic model of the vehicle fleet composition affected by EVs' policy measures is useful to get perspectives on the polarization of EVs as well as the GHG emission trend in the road transportation sector [6].

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Currently, the research methods for modeling the vehicle fleet composition in different countries and regions can be mainly divided into two categories: the system dynamics (SD) model and the agent-based model (ABM). The SD model serves as a top-down macro modeling approach to characterize the nonlinear behavior of complex systems over time. Stocks, flows, feedback loops, table functions, etc. are utilized to illuminate causal relationships among diverse system elements. The system's inherent behaviors including evolutionary processes, interplays, and hysteresis phenomenon are then simulated. Consequently, the SD model is suitable for predicting the medium-term and long-term development scale of vehicle fleet and its composition at the macro scale [7,8]. The growth rate of vehicle stock in the SD model is the key parameter to predict vehicle sales. Meanwhile, the discrete choice model (DCM) is embedded to estimate the market share of vehicles with different attributes [9-11]. The DCM is usually derived under an assumption of utility-maximizing behaviors to describe decision makers' choices among alternatives [12]. In this case, a utility function is incorporated to characterize the features of potential choices and subjects. The utility for an individual purchasing a vehicle is a satisfaction function of observed features of the individual, observed features of the vehicle, and an error term representing unobserved attributes [13-16]. For example, A DCM was put forward with a utility function, which includes vehicle attributes such as vehicle price, fuel cost, maintenance cost, battery replacement cost, driving range, and fuel availability, to depict preferences of consumers in various groups [17,18]. In the simplest case of a linear utility function, the coefficients associated with the features and their interaction are estimated by statistical data fitting. For instance, it is feasible to fit a conditional logit model looking at the probability of actual purchased vehicle model in pairwise comparisons as a function of fuel type and individual characteristics. To sum up, DCMs operate at the level of individual decision-makers, but aggregate measures, such as the average probability within a population or the average response to a change in some factors. Therefore, DCMs are not suitable to reflect the mutual influences among individuals.

In comparison, the ABM is a bottom-up simulation approach that predicts vehicle fleet composition and GHG emissions at the micro level. The ABM commences with the simulation of individual agents and subsequently aggregates their actions and interactions to provide insights into the macro outcomes [9]. Various agents, including government, fuel companies, car manufacturers, and car users have been considered in the current ABM based research for the automobile electrification progress [7,19-22]. Each agent in the model is endowed with a set of behavioral rules that guide their decision-making and help them response to the changes in external parameters. The agents of the same type share some common behavioral rules while allowing for a certain degree of personalization based on the individual attributes of the agents. Usually, agent attributes are selected within a hypothetical specified scenario. For example, the assumption that users choose the least purchase-cost vehicle are widely adopted, in which the use-cost difference cause by the incentives are ignored. Therefore, the behavior rules and decision-making of agents in the model are simplified, which sometimes causes deviation from the real-world scenarios. Pasaoglu et al. constructed an ABM with lowest cost selection strategy, which aimed at better understanding and analyzing market trends of light duty vehicle [19]. However, the environmental benefits of consumers are not considered. In addition, another motivation for the simplification of ABMs is that a large number of sophisticated individual-level agents call for significant computational resources and time, which limit the model's scale and applicability. Hence, exploring the heterogeneity degree of agents in ABMs is useful to truly mirror real-world complexities.

To sum up, the SD model cannot reach the individual scale, while the ABM simplifies user behavior and requires significant computational time. Therefore, some scholars have begun to combine the two methods and improve them [22,23]. By combining SD and ABM, some components can be modelled discretely and in a disaggregated way, while other components can be modelled continuously and in an aggregated way, based on the different system characteristics and the specific model purpose. In this way, a hybrid SD-ABM model facilitates the definition of appropriate levels of aggregation for each component of the system. Furthermore, the combination of SD and ABM can reduce computational time, while capturing relevant elements of the individual heterogeneity and stochasticity of entities and processes. However, certain hybrid SD-ABM models for transportation sector assume that user attributes and preferences follow independent empirical distributions [24-26]. This assumption cannot fully capture the complex interplay of attributes and preferences in real-world scenarios, in which real-world user behavior is often affected by a combination of various factors. Hence, these models are mostly applicable to mature and stable markets, and it is difficult to simulate the drastic changes in emerging markets. The EV market is an emerging and rapidly changing market due to various factors such as subsidy withdrawal and technological advancements. Quantifying and incorporating these mutation factors into the model have become a current challenge. Moreover, the intensity of the implementation of various usage-based incentives after the subsidy withdrawal has also become a research concern.

Therefore, this paper aims to establish a combined framework of SD and ABM to predict the EV penetration and GHG emissions in the private passenger vehicle sector under the influence of different combinations of policy scenarios. GHG emissions from the fuel cycle are the focus of this paper because they account for 60-70% of the vehicle's total lifecycle GHG emissions and have a large reduction potential [27]. The main innovations are as follows: (1) A comprehensive SD-ABM framework that integrates government, enterprise, and consumer interactions, has been designed to analyze the evolving dynamics among these entities through their mutual influences and interactions. (2) A novel data-driven approach for user classification is proposed to accurately characterize user heterogeneity. This approach enhances the model's sensitivity to rapid market changes and facilitating a detailed evaluation of policy impacts on varied car user segments. (3) A quantitative assessment of the potential GHG emissions reduction from usage-based incentives in the road transportation sector is carried out, offering strategic guidance for the implementation of incentives including OC, V2G, PCT for road transport, and battery recycling.

The remainder of this paper is organized as follows: Section 2 proposes the SD-ABM model and describes the content and interconnections of each sub-model. Section 3 validates the model, analyzes the results of different scenarios, and performs sensitivity analysis on related factors. Finally, in Section 4, the conclusive insights and policy implications are derived from this study.

2. Methodology

2.1 Overall framework of SD-ABM model

This paper develops a system dynamics-agent-based model (SD-ABM) to analyze the greenhouse gas (GHG) emissions from the private passenger vehicle sector in China. The SD-ABM model aims to mirror user behavior, the impact of government-led incentives on users, and the resulting market changes. A data-driven ABM is proposed to categorize distinct behavioral patterns of agents, serving as foundational input for the SD model. In the ABM, average annual energy consumption rate (ECR) and annual driving mileage have been picked as the most crucial features of the agent for classifying car users. To begin, a data-driven method is employed to precisely calculate ECR based on monitoring EVs data. Subsequently, a sophisticated two-dimension user classification is implemented, in which annual driving mileage and ECR are considered simultaneously. In this scenario, EV cost-saving measures adoption are induced to evaluate the impact of OC and V2G on encouraging the EV popularization.

The behavioral data from the agent-based model (ABM) are injected into the system dynamics (SD) model as factors. The SD model mainly investigates the impact of these factors on the subsystems. The SD model mainly consists of three subsystems: the ICEV and EV cost subsystem, the R&D subsystem, and the consumer market subsystem. The ICEV and EV cost subsystem analyzes the use-phase cost, which is affected by users' behaviors, for agents to use ICEVs and EVs, respectively. The R&D subsystem considers government subsidies and technological innovation of enterprises to calculate acquisition costs. The use-phase cost and acquisition cost together make up the life cycle cost (LCC) of vehicles. The consumer market subsystem links LCC and users' vehicle purchasing decisions. The vehicle ownership prediction model describes the constraints of economic development on the capacity of the automotive market. Finally, combining vehicle fleet composition, vehicle ownership, and GHG emission calculation method, the total GHG emissions in the driving phase of the private passenger vehicle sector can be outputted.

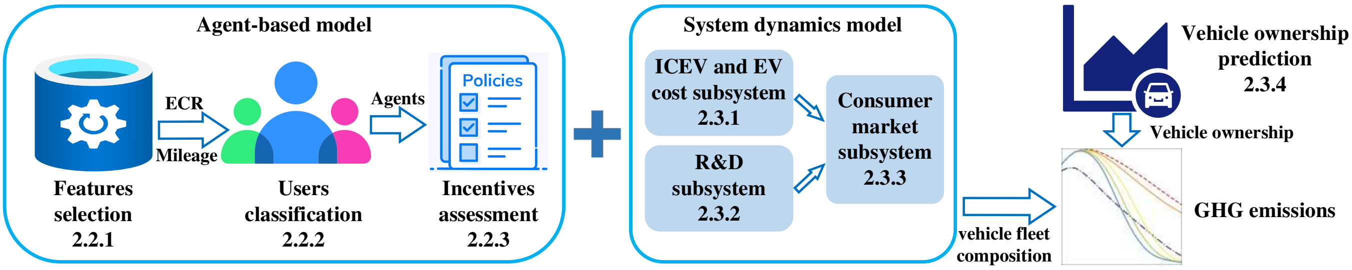

Fig. 1. Overall framework of SD-ABM model.

2.2 ABM

As a vehicle user, the operational costs during the utilization phase mainly depend on the ECR and mileage. The fuel consumption rate of ICEV is converted through the ECR of an equivalent electric vehicle, based on the principle of energy equivalence. With the alleviation of range anxiety of EVs, a presumption is made that the driving mileage for both ICEVs and EVs is equal. To calculate use-phase cost accurately, the ECR and mileage of each user are derived from odometer readings and remote monitoring data. Subsequently, a refined classification based on ECR and mileage becomes pivotal for the ABM. Specifically, the OC and V2G serve as measures to reduce the EV use-phase cost. A data-driven method is induced to calculate the cost saving of OC and V2G. In addition, the introduction of V2G is anticipated to expedite battery degradation, indirectly impacting the usage cost, which becomes a factor that should be taken into consideration.

2.2.1 ECR calculation of EVs

Given the substantial disparities between officially declared ECRs of EVs and their actual values, enhanced precision can be achieved by leveraging real-world operating data for ECR calculations. The operational data of all electric private passenger vehicles in China, sourced from the National Big Data Alliance of New Energy Vehicles Lab, is utilized for model establishment. This dataset spans from 2017 to 2021 with a sampling interval of 10 seconds. Acknowledging potential errors in data transmission, robust data processing methods outlined in Supplementary 1.1 are employed to ensure validity and accuracy of the information. The data is categorized into charging, parking, and driving segments. The segmentation process and state identification for real-world operating data is detailed in Supplementary 1.1. Subsequently, the charging and driving segments can be aligned to accurately calculate the ECR.

Usually, the ECR of an electric vehicle is defined as the energy consumed from the battery per 100 kilometers traveled, as illustrated in equation (1).

$$ECR = \frac{E}{d_{trip}} \quad (1)$$

where d_{trip} represents the driving mileage of a driving segment, and E denotes the energy consumed from the battery.

The data required for ECR calculation includes voltage, current, time, and state of charge (SOC) of charging segments, along with SOC and cumulative driving distance of driving segments. Two distinct methods exist for calculating energy E. The first involves employing the ampere-time integration method for driving segments, notwithstanding the considerable voltage and current fluctuations during such segments. The alternative method involves applying the ampere-time integration method for charging segments and subsequently multiplying by the charging efficiency [28,29]. Given the correlation between charging and driving segments, the latter method is used in this study for precise energy calculations. The starting and ending SOC of the charging segments are utilized to facilitate the accurate calculation of d_{trip}. The detailed procedure for ECR calculation is explicated in Supplementary 1.2.

2.2.2 User classification

Vehicle purchasing decisions made by users are increasingly affected by use-phase cost, which are intricately linked to usage attributes such as ECR and mileage. It is valuable to integrate a substantial amount of real-world operating data from users to enhance the precision of user categorization based on ECR and mileage. The user classification predominantly employs statistical methods, incorporating probability density. Probability distribution can be differentiated into independent empirical distribution and multivariate joint probability distribution. The independent empirical distribution ignores the correlation between attributes and is unsuitable for multi-dimensional user classification. Therefore, a multivariate joint probability distribution for ECR and mileage is established utilizing real-world operating data. Additionally, data-driven method are integrated with user classification, enabling the attribute values of user agents to evolve over time and can be used for predictions in subsequent years.

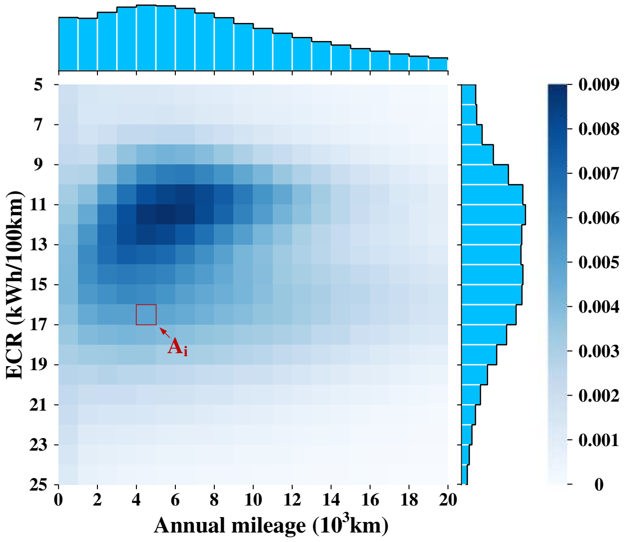

Fig. 2. The annual mileage and ECR of agents in 2021 (The color indicates the weight of each agent).

The distribution of average annual ECR and annual driving mileage for all users in 2021 is illustrated in Figure 2. The distribution is discretized into a grid, where each cell is considered as an agent (denoted as A_i in Figure 2). The average of the annual mileage and ECR of all users in the cell, affecting the use-phase cost, characterize the agent for subsequent decision making in the SD model. Through statistical analysis spanning 2017 to 2021, it is observed that due to advancements of vehicle technology, the annual ECR is reduced by 3.759% relative to the previous year, serving as the basis for subsequent ECR assumptions. Notably, owing to lockdown measures during the epidemic, ECR is an average value unaffected by COVID-19, while mileage is a cumulative value influenced by COVID-19. In essence, using the extension of mileage as a future assumption is inappropriate. Consequently, the annual mileage of each agent is hypothetically predicted based on relevant literature [14]. Hence, the attributes of each agent dynamically evolve from year to year. Diverse user attributes lead to different choices of fuel types (see Section 2.3.2). The presented approach, when coupled with the subsequent SD model, holds the capability of capturing the varied responses of consumers to usage-based incentives, in contrast to a global average approach without user classification, ,.

It is worth mentioning that this article assumes similarity in the distribution of usage attributes between potential car owners and existing car owners. Each user agent will be incorporated into the subsequent SD model to simulate the decision-making process. The population proportion of each agent category for the subsequent SD model is shown in equation (2). Here, N_i represents the number of users within each agent category, and γ_i denotes the population proportion of each agent category.

$$\gamma_i = \frac{N_i}{\sum_{i=1}^{I} N_i} \quad (2)$$

2.2.3 Incentives assessment

For car users, there are costs associated with converting fuel energy into driving mileage. Ordering charging facilitates the purchase of the same amount of electric energy at a reduced cost, while Vehicle-to-Grid enables users to sell excess electricity for additional income. The cost savings linked to OC and V2G participation significantly impact on the overall usage cost, so they must be considered in the users' decision-making process. Together with the previously discussed Energy Consumption Rate (ECR) and mileage, OC and V2G emerge as pivotal components of the usage attributes. Assuming that charging schedulability and cost savings for potential car owners mirror those of existing car owners, it is essential to explore the cost-effectiveness of OC and V2G participation across user agents with diverse usage attributes. This investigation is crucial for comprehending the influence of usage-based incentives on users' vehicle purchasing decisions [30,31].

To ensure minimal impact on car usage, the OC and V2G is usually applied during parking times that include charging events, so the parking data analysis is focused. This section aggregates the parking data containing charging segments of EVs sourced from the National Big Data Alliance of New Energy Vehicles Lab. Given the similarity in charging energy and available time slots for charging within each agent category, all users within a category are aggregated and collectively optimized. Specifically, the optimization objective of the OC and V2G model is to minimize electricity purchase cost. Initially, parking durations with charging segments for all private passenger vehicles are extracted from the database, and the local time-of-use (TOU) electricity tariffs are investigated. Subsequently, the initial charging decision sequence is formulated by discretizing parking durations into 1-min intervals, where the charging state is regarded as 2 and the parking state is assigned as 1. The charging strategy problem is transformed into an integer linear programming problem, essentially adjusting the charging time of EVs to low-priced periods. Factoring in the initiation and conclusion times of parking, an iterative approach is employed to optimize the charging decision sequence using the CPLEX optimization tool. Ultimately, the optimal charging schedule and charging cost of EVs with V2G strategy are obtained.

Taking a parking segment of an EV that includes a charging segment as an example, the optimization objective and constraints are shown in equation (3) to (6):

$$\begin{cases} CC_t = (CS_t - 1) \times (DP_t - \dfrac{BP}{BC \times NE}) \times P_t & CS_t = 0 \\ CC_t = 0 & CS_t = 1 \\ CC_t = (CS_t - 1) \times TOU_t \times P_t & CS_t = 2 \end{cases} \quad (3)$$

$$\min \ CC = \sum_{t=1}^{T} CC_t \quad (4)$$

$$s.t. \quad \sum_{t=1}^{T} CS_t = \sum_{t=1}^{T} CS'_t \quad (5)$$

$$SOC_{min} \le SOC_t \le SOC_{max} \quad (6)$$

where CC represents the total charging cost in this parking segment, while CC_t, DP_t, and P_t represent the charging cost, discharging price, and charging and discharging power at minute t. T represents the parking duration. Assuming that the discharging price is 1.34, 1.39, and 1.64 times of the charging price at peak time, normal time, and valley time, respectively [32]. CS_t and CS'_t represent the charging decision variable and its initial state at minute t, where 0,1,2 represent discharging, stopping, charging state, respectively. BP, BC, and NE represent battery price, number of battery cycles, and nominal energy, which are used to characterize the battery degradation resulting from the discharge of the EV involved in V2G. Equation (5) represents the energy constraint that ensure no impact on the user's driving demand, while equation (6) is the State of Charge (SOC) constraint preventing the battery from overcharging and overdischarging. Relevant parameters are shown in Supplementary 2.1.

2.3 SD model

The government, enterprises, and consumers are defined as the main stakeholders in the SD model (see Figure 3). In their role as policymakers, the government relies on manufacturers and consumers to expedite EV industrialization. The primary function of the government is to offer R&D subsidies to enterprises and adjust purchase subsidies and usage-based incentives for consumers based on EV promotion objectives. As EV supplier, vehicle enterprises determine their investments in the production and research of EVs based on the government R&D subsidy and consumer demand. Consumers play a pivotal role in EV diffusion and make purchase decisions after comprehensively evaluating purchase subsidies and usage-based incentives.

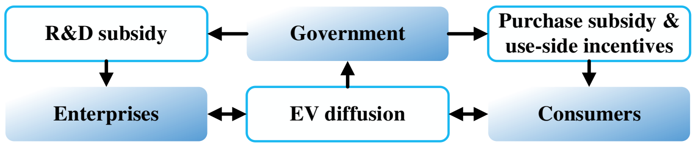

Fig. 3. Influence mechanism of different stakeholders on EV diffusion.

To analyze the impact of various incentives on the market share of sales and GHG emissions in the private passenger vehicle sector following the subsidy withdrawal, it is essential to clarify their influence on consumers' vehicle purchasing decisions. These decisions are inherently tied to the LCC of EV and ICEV, as shown in the consumer market subsystem in Figure 4. LCC primarily encompasses acquisition cost and use-phase cost. Acquisition costs depend mainly on government subsidies and technological innovation from enterprises, as illustrated in the R&D subsystem in Figure 4. Given the relatively fixed nature of acquisition costs, this study focuses on use-phase costs, as outlined in the EV and ICEV cost subsystems in Figure 4.

Considering numerous pivotal factors in each subsystem, this study constructs a flow diagram to delve into the interplay among these critical factors, as shown in Figure 5. The diagram contains 55 variables: 3 level variables, 5 rate variables, 15 constant variables, and 32 dynamic variables. It illustrates the mutual influences and interaction relationships among these factors, with arrows indicating the influence of interactions. Meanwhile, the input and output relationship between ABM and SD is depicted in Figure 5. Due to space constraints, the following sections will describe the significant aspects of the presented model, with additional equations and explanations provided in Supplementary 2.3. A key highlight of this section is the dynamic adjustment of SD-ABM model parameters using the data-driven method to adapt to drastic changes in emerging markets. Additionally, this SD-ABM model can integrate the results from V2G and other models, demonstrating strong scalability.

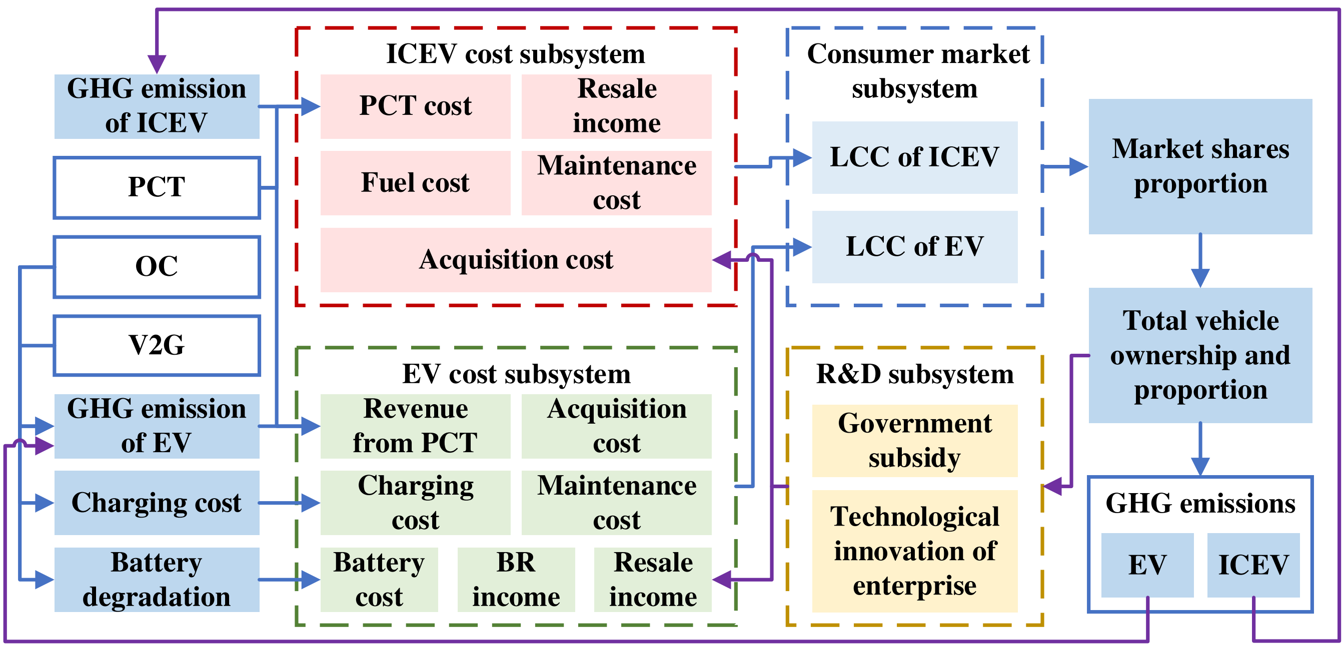

Fig. 4. The SD model.

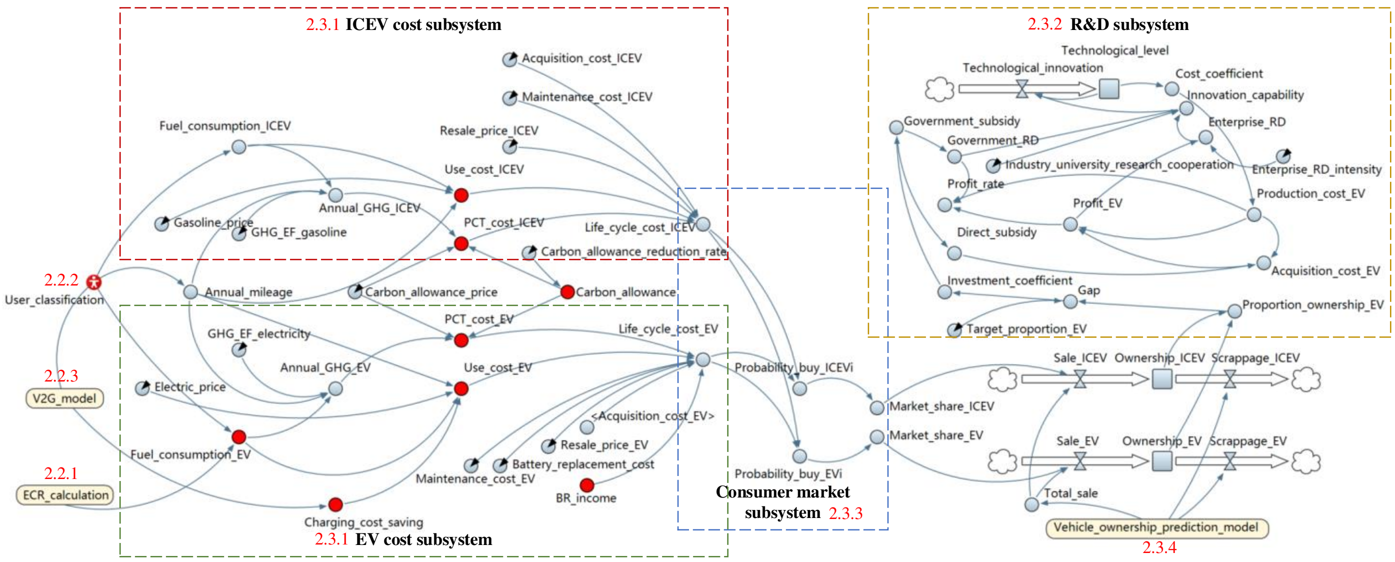

Fig. 5. Flow diagram of the SD-ABM model (The red variables and the yellow modules are the highlights of this SD model).

2.3.1 ICEV and EV cost subsystems

To commence the description of the cost subsystem, it is important to note that the consideration of Personal Carbon Trading (PCT) in this paper involves the government allocating a specific carbon allowance to each user within the scenario of road transport. Due to the diverse patterns of user usage, resulting GHG emissions also display variability. Users with surplus carbon allowances can trade the excess with those falling short of the standard, thus gaining a certain profit. The specific formulas and variables are provided in Supplementary 2.3.

Given the inclusion of PCT, the life cycle cost of ICEV mainly includes acquisition, maintenance, usage, resale price, and the cost of PCT. Meanwhile, the LCC of EV encompasses these aforementioned costs alongside charging savings, battery replacement cost, and battery recycling income, as illustrated in Figure 6. The LCC of EV (LCCE) is calculated by equation (7).

$$LCCE = ACE - RPE - PS + MCE + CCE + PCE + BRC - BRI - BVG \quad (7)$$

Here, the Acquisition Cost of EV (ACE), Resale Price of EV (RPE), Purchase Subsidy (PS) are determined by government and enterprises. Meanwhile, the Maintenance Cost of EV (MCE), Charging Cost of EV (CCE), PCT Cost of EV (PCE), Battery Replacement Cost (BRC), Battery Recycling Income (BRI), and Benefits of V2G (BVG) are collectively referred to as use-phase cost. The ABM is employed to specifically analyze the differences in use-phase cost. Under the OC and V2G scenarios, various agents experience distinct benefits from scheduled charging and encounter different levels of battery degradation, resulting in diverse charging costs and battery replacement expenses. Notably, the charging cost and battery degradation of different agents vary drastically along with scenarios.

$$PCE = (GE - CQ) \times LE \times ACP \times PPF \quad (8)$$

The PCT cost of EV is related to GHG of EV (GE), Carbon Quota (CQ), Life of EV (LE), Average Carbon Price (ACP), and PCT Promotion Factor (PPF), as shown in equation (8).

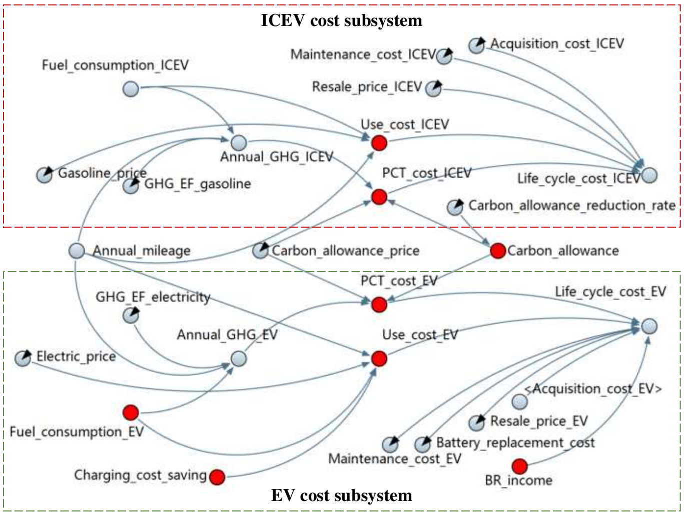

Fig. 6. Flow diagram of ICEV and EV cost subsystems.

2.3.2 R&D subsystem

The R&D subsystem is driven by the disparity between the current proportion of EV ownership and targeted proportion. It elucidates the impact of technological innovation, government policies, and enterprise R&D capability on the production cost of EVs [14-16]. As depicted in Figure 7, the government adjusts subsidy policies in response to the gap between the proportion of EV ownership and targeted proportion, affecting the investment coefficient in the subsystem. The investment coefficient is directly proportional to the total amount of subsidy. The higher the disparity between the actual EV penetration rate and the target, the greater the investment coefficient. A portion of the subsidy is allocated to purchase subsidy, while another portion is utilized to foster technological innovation through industry-university-research cooperation. Simultaneously, as enterprises benefit from the enhancement of their innovative capabilities, a portion of their profits from EV sales is typically invested in R&D activities. With continuous technological advancement and improvements in production efficiency, a reduction in the production cost of vehicles is anticipated, as reflected by the cost coefficient in the model. Under the premise of ensuring a relatively constant profit margin for the enterprises, this process also contributes to the reduction of acquisition costs. The key formulas for these interactions are as follows.

$$TL(t) = \sum_{t=0}^{T} TI(t) + TL(t_0) \quad (9)$$

$$TI = IC \times TL \quad (10)$$

$$IC = (GR + ER) \times IURC \times 0.00001 \quad (11)$$

The Technological level (TL) is related to its initial value and technological innovation (TI) in equation (9). TI, in turn, depends on TL and innovation capability (IC) in equation (10). Moreover, IC can be predicted by government R&D (GR), enterprise R&D (ER), and industry-university-research cooperation (IURC).

In this paper, it is observed that incentives for users yield more significant effects than those for car manufacturers, which is in line with finding in the literature [19,33]. Therefore, this subsystem is not the primary focus of this study, and specific parameters and calculation methods can be referenced from previous works [14-16].

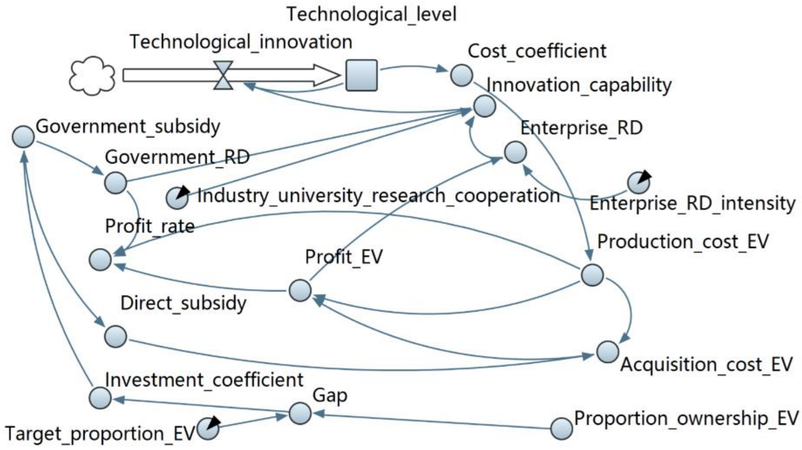

Fig. 7. Flow diagram of R&D subsystem.

2.3.3 Consumer market subsystem

to understand how market penetration changes over time, it is important to model the purchasing decisions of consumers. In the consumer market subsystem, the probability of purchasing EVs for each agent depends on the environmental friendliness of the vehicle, the LCC of EVs, the LCC of ICEVs, and license plates restrictions for ICEVs, as shown in Figure 8. Consequently, the market share of EVs is obtained by multiplying the purchasing probability and the weight of each agent defined by equation (2). The probability of purchasing EVs for each agent and the market share of EVs is shown in equation (12) - (15):

$$\theta_{EV,i} = \frac{\tau_{EV} \times LCC_{EV,i} - \tau_{ICEV} \times \left(LCC_{ICEV,i} + T_{ICEV}\right)}{g_{EV} - g_{ICEV}} \quad (12)$$

$$\theta_{ICEV,i} = \frac{\tau_{ICEV} \times \left(LCC_{ICEV,i} + T_{ICEV}\right)}{g_{ICEV}} \quad (13)$$

$$PPEV_i = \frac{1-\theta_{EV,i}}{1-\theta_{ICEV,i}} \quad (14)$$

$$MSE = \sum_{i=1}^{I} \gamma_i \times PPEV_i \quad (15)$$

where i denotes the i-th agent. g_{EV} and g_{ICEV} represent the environmental friendliness of EVs and ICEVs, respectively; θ_{EV} and θ_{ICEV} represent consumers' environmental awareness of purchasing EVs and ICEVs; τ_{EV} and τ_{ICEV} represent consumers' sensitivity to EV and ICEV prices, which are obtained by Genetic Algorithm (GA) using sales data from 2014 to 2022; T_{ICEV} represents the degree of license plate restrictions for ICEVs; $PPEV$ represents the probability of purchasing EVs, and MSE represents market shares of EVs. In summary, the ABM is integrated with SD to provide a more comprehensive representation of the impacts of incentives on the population and accurately predict the market penetration of EVs.

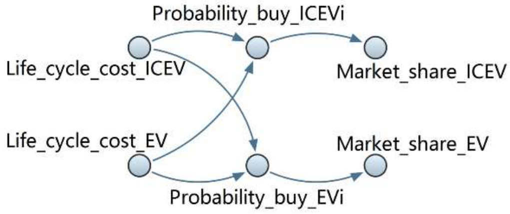

Fig. 8. Flow diagram of consumer market subsystem.

2.4 Vehicle ownership and GHG emissions prediction

To analyze the composition of the fleet in the private vehicle sector, it is important to consider not just users' vehicle purchasing decisions but also the factors influencing fleet renewal, including the survival and retirement rates of vehicles. The significance of this section lies in considering the retirement rate of vehicles in different years, which makes the dynamic changes in fleet composition more realistic compared to other relevant literature. Furthermore, considering the change in vehicle ownership is valuable for projecting GHG emissions afterwards.

In this paper, the Gompertz function (16) is used to describe the relationship between GDP per capita and vehicle ownership per capita. The validity of this model has been confirmed by many studies [34-36]. Notably, Gompertz model requires less data and is particularly suitable for developing countries.

$$VOPC_y = VOPC^* \times \exp(\alpha \times \exp(\beta \times GDPPC_y)) \quad (16)$$

Where $VOPC_y$ is the vehicle ownership per capita in the year y, $VOPC^*$ is the final target of vehicle ownership per capita, and $GDPPC_y$ is the per capita Gross Domestic Product (GDP) in the year y. The values of α and β are calculated using a genetic algorithm (GA) based on official data from 2010 to 2021. And the parameters can be further adjusted based on subsequent annual data to perform a rolling fit. Relevant parameters are outlined in Supplementary 2.2.

Subsequently, the methodology for forecasting annual vehicle retirement, vehicle ownership, and total sales of vehicles are expressed through the following equations (17) - (19):

$$VO_y = VOPC_y \times PP_y \quad (17)$$

$$VR_y = \sum_{t=y-LC}^{y} TSV_t \times RR_{y-t} \quad (18)$$

$$TSV_y = VO_y + VR_y - VO_{y-1} \quad (19)$$

where VS_y, VO_y, TSV_y and PP_y represent the vehicle retirement, vehicle ownership, total sales of vehicles, and projected population in the y year, respectively [15]. LC represents the life cycle of vehicles. RR_{y-t} denotes the retirement rate of vehicles in the $y-t$ year (see Figure 9). Certainly, in the absence of sufficient data on the survival curve for EVs spanning less than 10 years, it becomes challenging to provide a definitive estimate for this curve. Therefore, it is assumed that the survival curve for EVs is the same as that for ICEVs[37,38]. In general, vehicle ownership is predicted by GDP. The determination of vehicle retirement relies on the sales volume from preceding years, considering the corresponding retirement rate. Subsequently, the total sales of vehicles are calculated from vehicle ownership and vehicle retirement, as shown in equation (19).

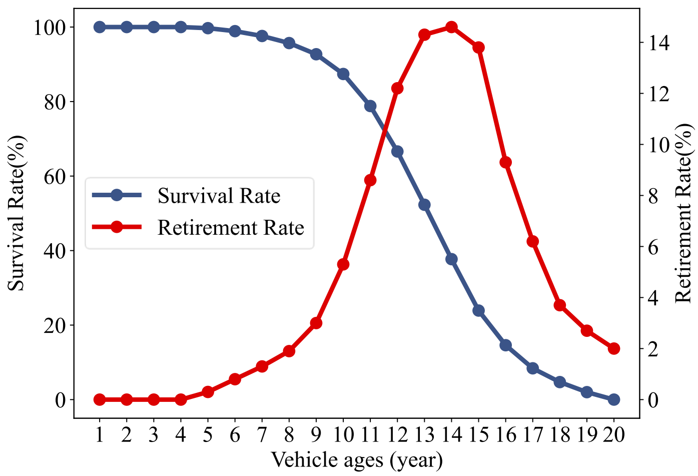

Fig. 9. Survival rate and retirement rate of private passenger vehicles in China [37,38].

Finally, the annual GHG emissions in the private passenger vehicle sector can be obtained:

$$GHG_y = VO_{EV,y} \times EF_{e,y} \times \overline{M_{EV,y}} \times \overline{ECR_y} + VO_{ICEV,y} \times EF_{g,y} \times \overline{M_{ICEV,y}} \times \overline{FC_y} \quad (20)$$

where $VO_{EV,y}$ and $VO_{ICEV,y}$ represent vehicle ownership of EVs and ICEVs in year y, respectively. $EF_{e,y}$ and $EF_{g,y}$ represent the GHG emission factor of electricity and gasoline in year y, respectively. $\overline{M_{EV,y}}$ and $\overline{M_{ICEV,y}}$ are the average mileage of EVs and ICEVs in year y. $\overline{ECR_y}$ is the average annual ECR of EVs in year y, and $\overline{FC_y}$ is the average annual fuel consumption per 100 kilometers of ICEVs in year y.

3. Results and discussion

In this section, the effectiveness of the SD-ABM model is validated using historical sales data. The projected market share of Electric Vehicles (EVs) and Greenhouse Gas (GHG) emissions are compared across multiple scenarios. This comparison provides insight into the specific policy measures needed to align with carbon reduction goals.

3.1 Model Validation

The SD-ABM model was validated by comparing the actual market shares of EVs from 2014 to 2022 with the model's simulated outcomes. This comparison, as illustrated in Figure 10, demonstrates a acceptable aliment between the real and simulated EV market shares, confined within a small variance range. Furthermore, the accuracy of predictions using the combined SD-ABM approach is significantly improved compared to those utilizing the SD method alone. This result supports the integration of SD and ABM methods for a more precise representation of market dynamics in real-world scenario.

The SD-ABM model proposed in this study employs a data-driven approach, incorporating a diverse set of real-world user data to capture user preferences and attributes comprehensively. The model predicts the probability of different types of consumers making distinct vehicle purchasing decisions, allowing for the characterization of the heterogeneous effects of various policies on different consumer segments. This fine-grained modeling is conducive to improving the sensitivity of the model to adapt to the drastic changes in emerging EV market. Therefore, the effectiveness and credibility of the proposed model pave the way for subsequent scenario analyses and predictions. Furthermore, the model offers flexibility for researchers and policymakers to update data from platforms or surveys, enabling parameter adjustments and iterative refinement of model results.

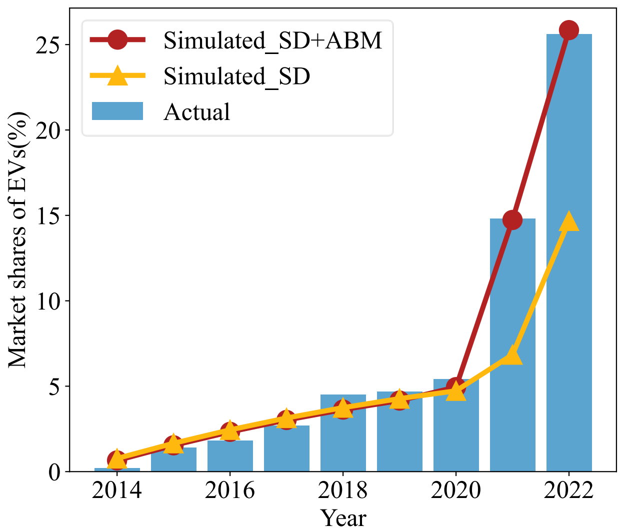

Fig. 10. SD-ABM model validation.

3.2 Analysis of different scenarios

3.2.1 Comparison of multiple scenarios

This paper focuses on analyzing the impact of usage-based incentives, including OC, V2G, PCT for road transport, and battery recycling, on the development of the EV industry, and compares these with the purchase subsidy policy. The specific scenarios and policy measures are detailed in Table 1.

Table 1

Scenarios and policy measures

Scenario	Policy measure
Baseline	The government does not provide financial support to EV manufacturers and buyers. There is no OC and V2G infrastructure, and users does not participate in the carbon trading market.
Subsidy	The government's approach involves adjusting financial support for electric vehicle (EV) manufacturers and buyers based on the variance between the expected target and the actual value of the EV market share until 2060.
OC	EV users' participation in OC follows the Gompertz curve, with the target of OC penetration rate in Technology Roadmap for Energy Saving and New Energy Vehicles 2.0.
V2G	EV users' participation in V2G follows the Gompertz curve, with the target of V2G penetration rate in Technology Roadmap for Energy Saving and New Energy Vehicles 2.0.
PCT	PCT for road transport is expected to be implemented in 2028, and the carbon price will be the same as the comprehensive carbon market.
BR	Retired batteries from EV users are recycled at a price of 150 RMB/kWh [39].

Initially, the baseline scenario primarily serves as a reference without targeted interventions. The subsidy scenario posits that the government will provide subsidies to manufacturers and users until 2060. The OC and V2G scenarios are modeled as OC4+V2G4 (refer to section 3.2.2 for details). Furthermore, the PCT for road transport is slated for implementation in 2028, and battery recycling is priced at 150 RMB/kWh, aiming for the private passenger vehicle sector to reach its carbon peak before 2030 under the combined usage-based incentives (OC+V2G+PCT+BR). Notably, due to the slower electrification of private passenger cars compared to commercial vehicles (such as taxis and buses), the road public transport sector is expected to reach its carbon peak ahead of the private passenger vehicle sector [40].

In Figures 11 through 16, solid lines represent scenarios involving usage-based incentives, while dotted lines correspond to the scenario involving a purchase subsidy policy. The round dots indicate the critical points when the market shares of EVs and GHG reduction benefits of the usage-based incentives scenarios exceed those of the purchase subsidy policy scenario, and the square dots indicate the carbon peaking points of the various scenarios.

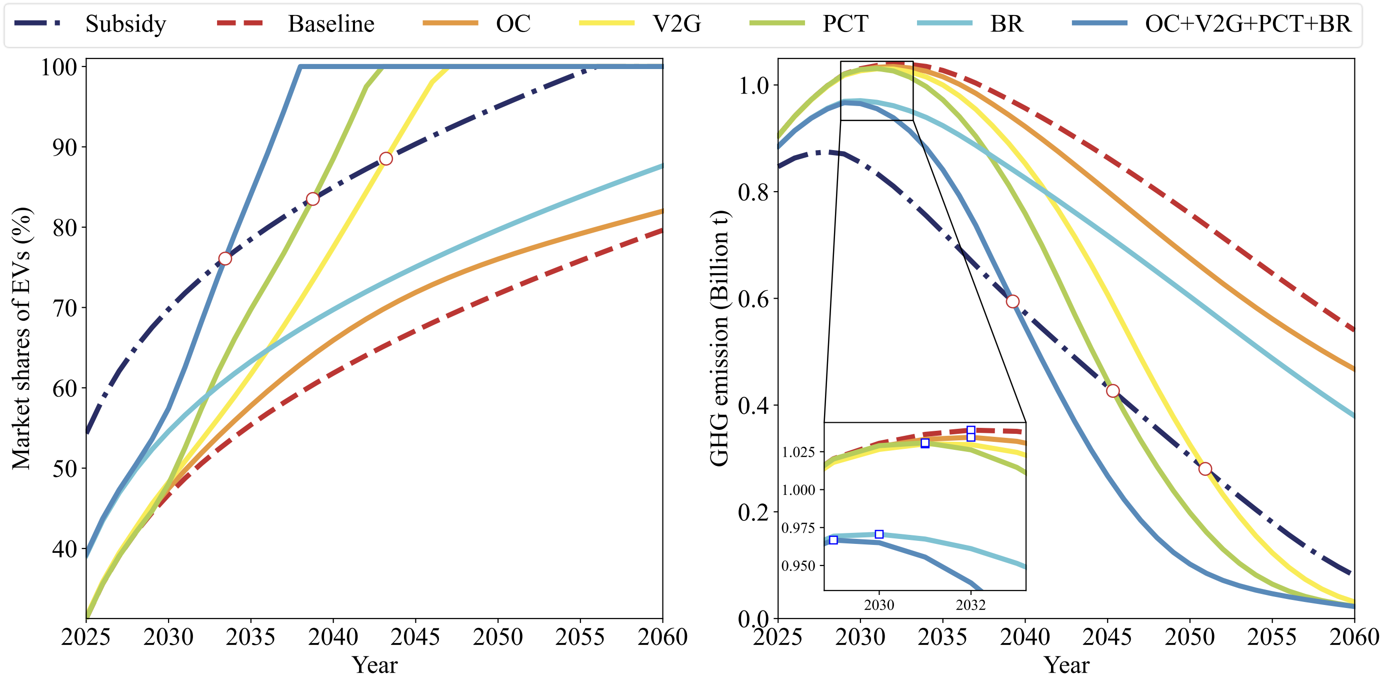

Fig. 11. Market shares of EVs (a) and GHG emissions of private passenger vehicle sector (b) in multiple scenarios.

Currently, the cost dynamics of EVs and ICEVs play a crucial role in influencing consumer purchasing decisions. The reduction of governmental financial support for EVs might place these vehicles at a competitive cost disadvantage within the automotive market. However, the deployment of usage-based incentives, including personal carbon trading (PCT) for road transport, effectively mitigates this issue. Specifically, the market shares of EVs in the Vehicle-to-Grid (V2G) and road transport PCT scenarios are projected to outstrip those in the purchase subsidy scenario by 2039 and 2043, respectively (as indicated in Figure 11(a)). Furthermore, by the year 2060, the V2G, road transport PCT, battery recycling, and purchase subsidy scenarios are expected to reduce Greenhouse Gas (GHG) emissions by 93.2%, 95.8%, 29.8%, and 85.1%, respectively, relative to the baseline scenario (refer to Figure 11(b)). Hence, while the purchase subsidy policy is advantageous for achieving an early peak in GHG emissions, strategies like V2G and PCT for road transport are more effective for long-term EV market penetration and substantial GHG emission reductions in the road transportation sector. Notably, among various demand-side policies, battery recycling stands out in the early stages of EV development. Moreover, the increasing market penetration of EVs reflects their growing acceptance among potential consumers.

Significantly, the envisaged market share targets for EVs outlined in "Technology Roadmap for Energy Saving and New Energy Vehicles 2.0" are attainable under all contemplated scenarios. Compared with PCT for road transport, the GHG reduction benefits brought by V2G are relatively modest. This is primarily attributed to the gradual promotion of V2G pile and the incremental increase in user participation in V2G programs, as detailed in Section 3.2.2. By 2040, it is projected that EVs will predominate in the consumer market, with the proportion of EV ownership anticipated to surpass 97.1% after 2050 under the combined usage-based incentives, thereby completing the electrification process within the private passenger vehicle sector.

3.2.2 Simulation program 1: OC and V2G

This part conducts a comprehensive quantitative analysis of the intensity of usage-based incentives necessary to facilitate the private passenger vehicle sector in reaching its carbon peak by 2030. Additionally, it aims to equate the GHG emission reduction benefits of these incentives with those derived from the purchase subsidy policy. Assuming that the adoption of OC and V2G practices adhere to the Gompertz curve, which is suitable for describing the generalization of techniques as shown in Figure 12 [41]. The various scenarios depicted in Figure 12 represent differential participation rates, with the foundational parameters for these scenarios being detailed in Table 2.

Table 2

Setting basis for various OC+V2G scenarios

Scenario	Setting basis
OC1+V2G1	OC and V2G technologies are developed 2 years ahead of the OC3+V2G3 scenario
OC2+V2G2	OC and V2G technologies are developed 1 year ahead of the OC3+V2G3 scenario
OC3+V2G3	Technology Roadmap for Energy Saving and New Energy Vehicles 2.0
OC4+V2G4	OC and V2G technologies are developed behind the OC3+V2G3 scenario by 1 year
OC5+V2G5	OC and V2G technologies are developed behind the OC3+V2G3 scenario by 2 years

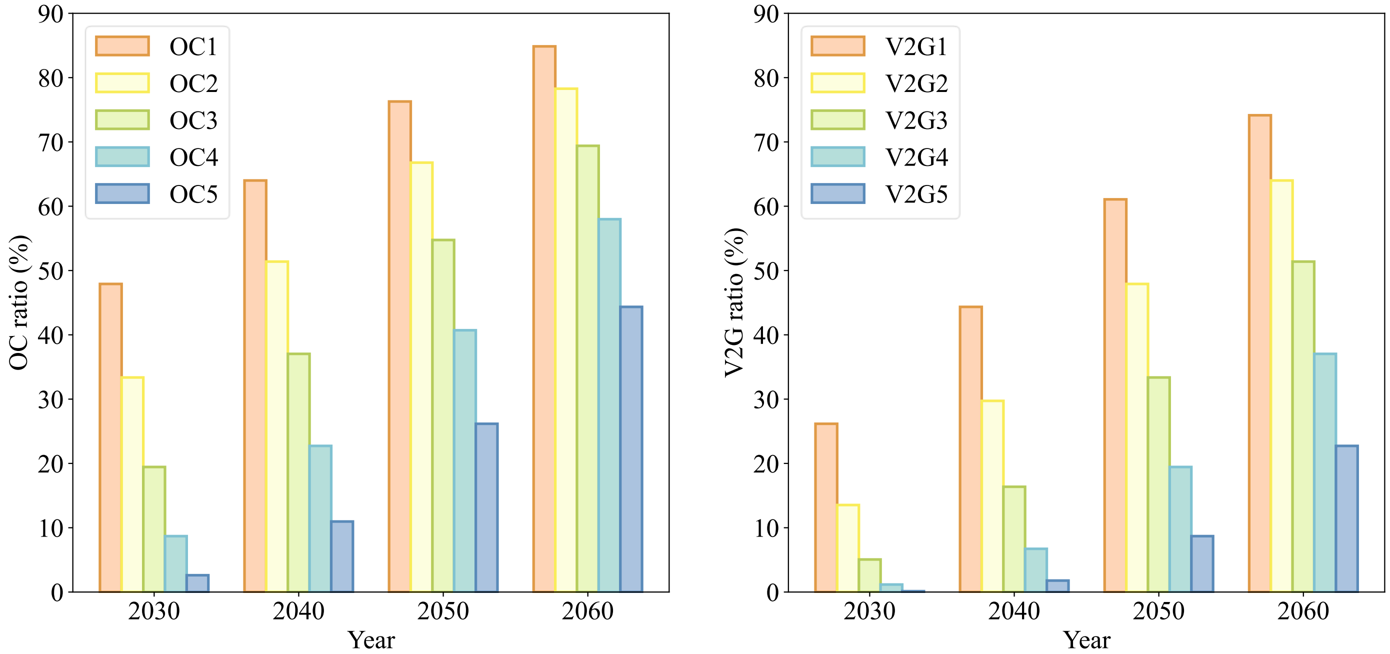

Fig. 12. Assumptions on the percentage of EV users participating in OC (a) and V2G (b).

The graphical representation of EV market shares and GHG emissions within the private passenger vehicle sector under various Orderly Charging (OC) and Vehicle-to-Grid (V2G) scenarios is depicted in Figures 13 and 14. These figures reveal that an increased adoption of OC and V2G is associated with decreased usage-phase costs for EVs, leading to an increasing market shares of EVs and an earlier attainment of GHG emissions peak, as well as a mitigation peak value within this sector. Comparing Figure 13(b) and 14(b), it becomes evident that achieving the carbon peak prior to 2030 is challenging without the incorporation of V2G technology. Specifically, Figure 14(b) highlights for the private passenger vehicle sector to reach its carbon peak by 2030 (as projected in the OC3+V2G3 scenario), the participation rates in Orderly Charging and V2G must reach 19.4% and 5.1%, respectively, resulting in a peak value of 1.013 billion tons. Therefore, if the technological milestones stipulated in the “Technology Roadmap for Energy Saving and New Energy Vehicles 2.0” are achieved, the sector is likely to achieve its carbon peak before 2030.

Moreover, as indicated in Figure 13, scenarios solely based on OC fall short in matching the EV market shares and GHG emission reductions observed with the purchase subsidy policy. This indicates the necessity of incorporating a significant proportion of V2G to fulfill the sector's GHG emission reduction objectives. Further, as demonstrated in Figure 14(b), scenarios with higher proportions of V2G have the potential to exceed the GHG emission reduction effects of the purchase subsidy policy at earlier stages.

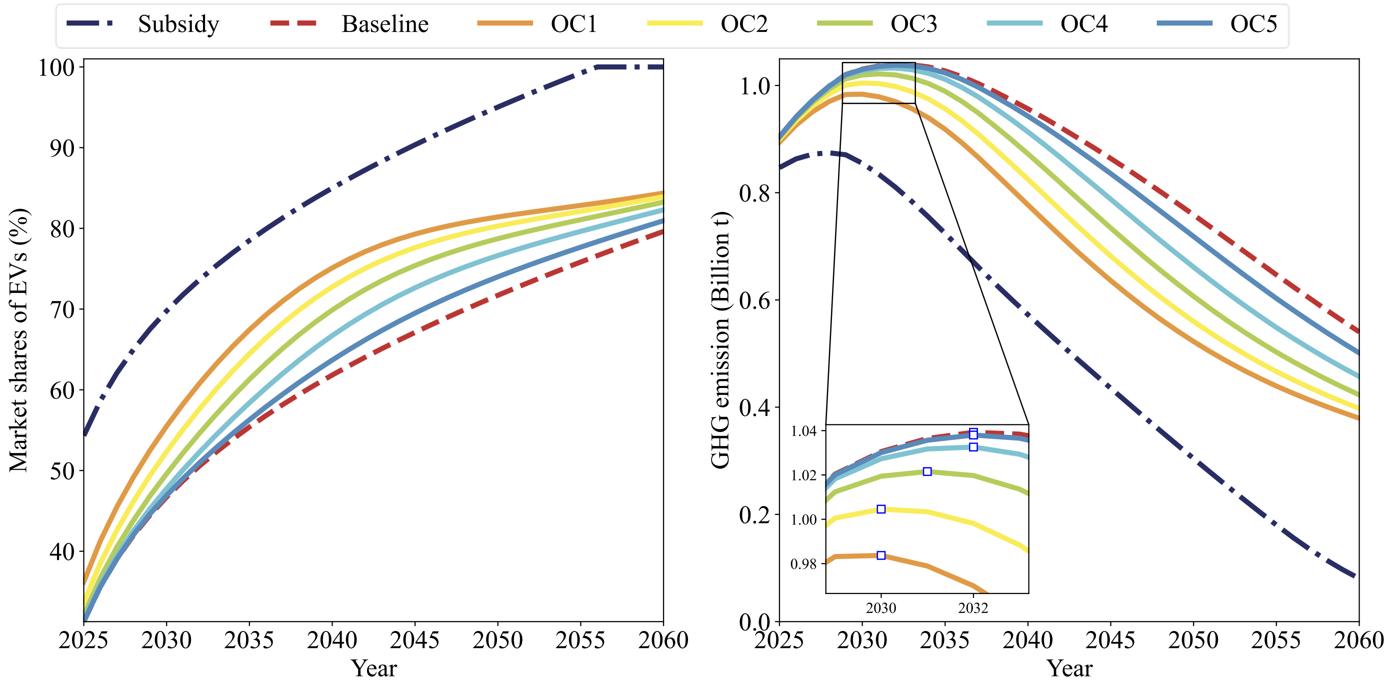

Fig. 13. Market shares of EVs (a) and GHG emission of private passenger vehicle sector (b) in different OC scenarios.

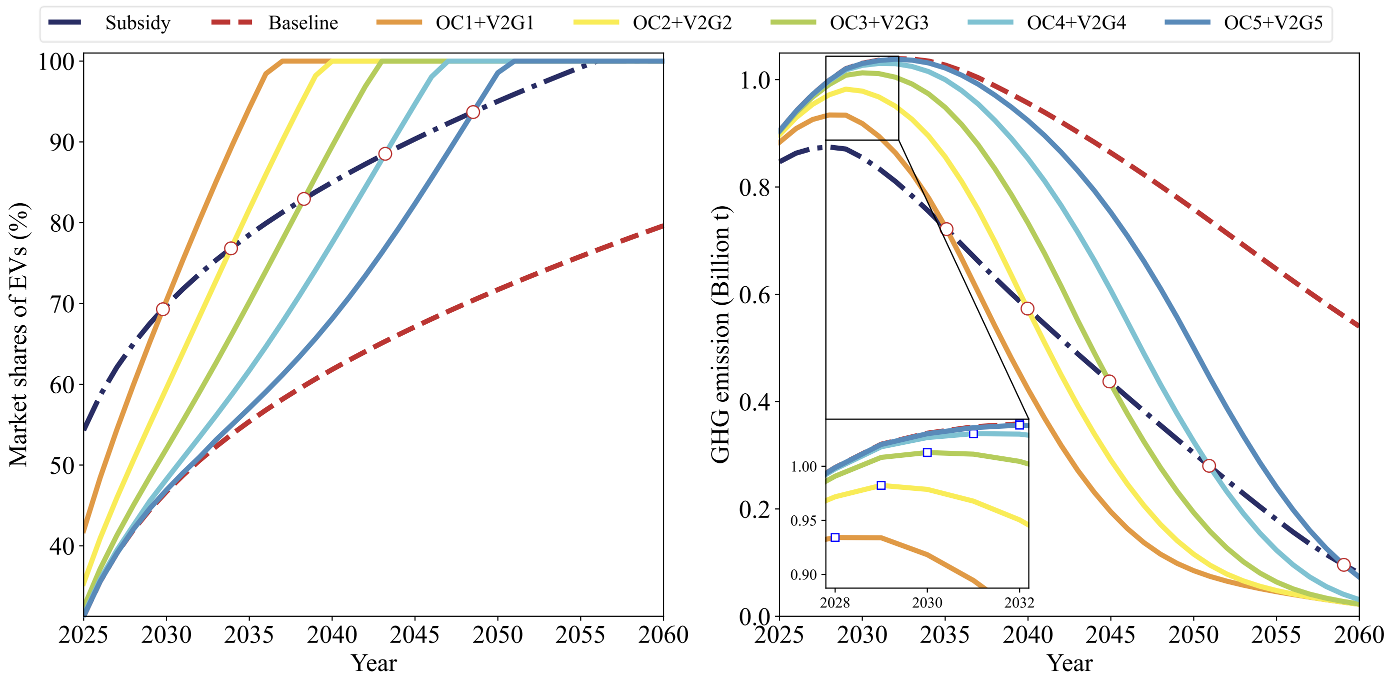

Fig. 14. Market shares of EVs (a) and GHG emission of private passenger vehicle sector (b) in different OC and V2G scenarios.

3.2.3 Simulation program 2: PCT for road transport

To analyze the impact of Personal Carbon Trading (PCT) for road transport on the diffusion of the EV market and its consequent effects on GHG emissions, this study varies the initiation years for implementing the PCT for road transport, thereby facilitating an analysis of the EV market's evolutionary trajectory as depicted in Figure 15. The designated initiation years are 2027, 2035, 2040, and 2045. A thorough examination of Figure 15 indicates that the early adoption of PCT for road transport significantly bolsters the market share of EVs and aids in curtailing the peak GHG emissions within the private passenger vehicle sector. Figure 15(a), the introduction of PCT for road transport shows a favorable impact on expediting the penetration of EVs. Notably, instituting PCT for road transport before 2027 is projected to contribute substantially to achieving the carbon peak by 2030, with an anticipated peak emission value of 1.026 billion tons. The initiation of PCT for road transport by 2035 is expected to have the market shares of EVs to 100% by 2043. Further, the implementation of PCT for road transport prior to 2040 is instrumental in advancing towards carbon neutrality by 2060. It is imperative to implement PCT for road transport no later than 2045 to ensure GHG emission reductions that are comparable to those achieved under the purchase subsidy policy by 2060, as elucidated in Figure 15(b). In conclusion, the rapidly evolving carbon trading market is effective in decelerating the expansion of ICEVs while concurrently fostering the growth of EVs.

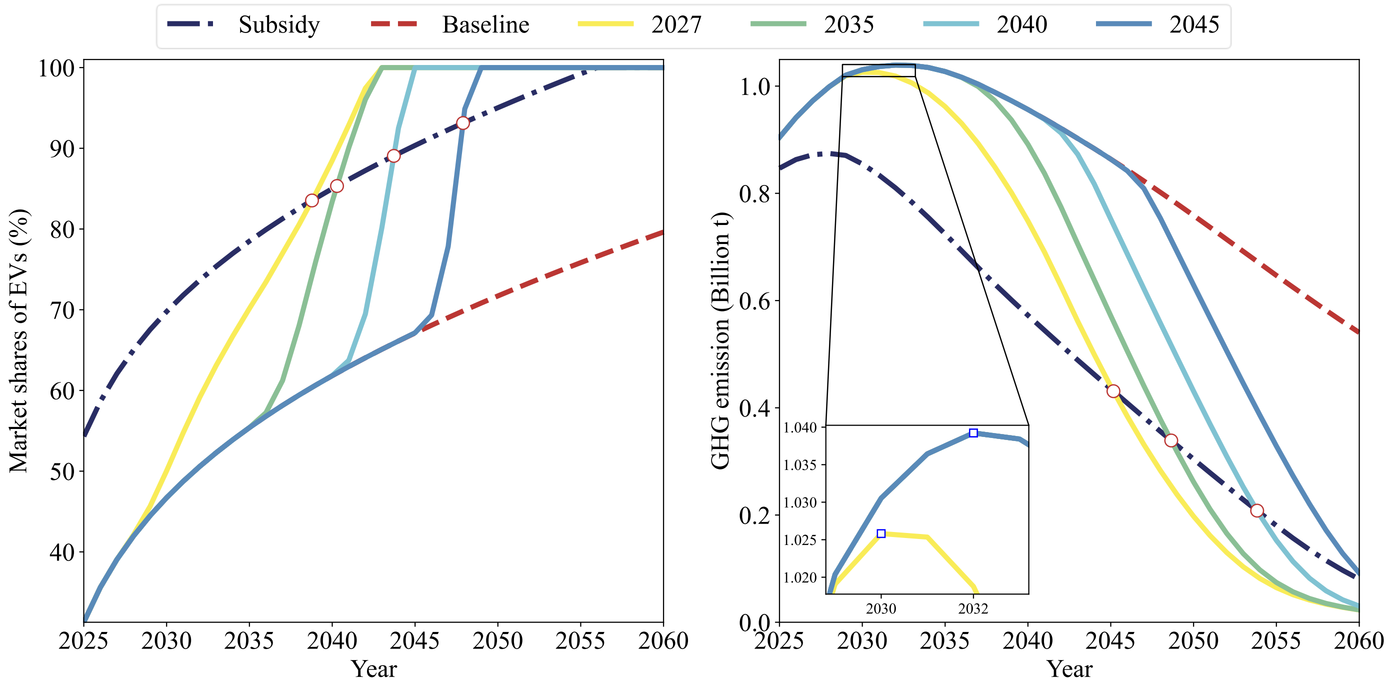

Fig. 15. Market shares of EVs (a) and GHG emission of private passenger vehicle sector (b) in different start years for PCT for road transport.

3.2.4 Simulation program 3: Battery recycling

This section aims at analyzing the effects of battery recycling remuneration on the EV industry by modifying the compensation rates for battery recycling and examining their influence on the EV popularization and GHG emissions, as depicted in Figure 16. The scenario is established where EV users can recycle their batteries for income once the battery capacity diminishes below 80%. The stipulated rates for battery recycling are set at 50 RMB/kWh, 100 RMB/kWh, 150 RMB/kWh, and 200 RMB/kWh. Comprehensive analysis of Figure 16 indicates that an escalated price for battery recycling positively correlates with an increase in the market share of EVs and a reduction in the peak GHG emissions within the private passenger vehicle sector. Notably, when the battery recycling price attains 100 RMB/kWh, the GHG emissions are projected to peak in 2030, reaching a value of 0.991 billion tons. In comparison to other usage-based incentives, battery recycling emerges as an effective short-term policy measure. However, scenarios relying solely on battery recycling fall short of achieving the EV market shares and GHG emission reductions observed under the purchase subsidy policy.

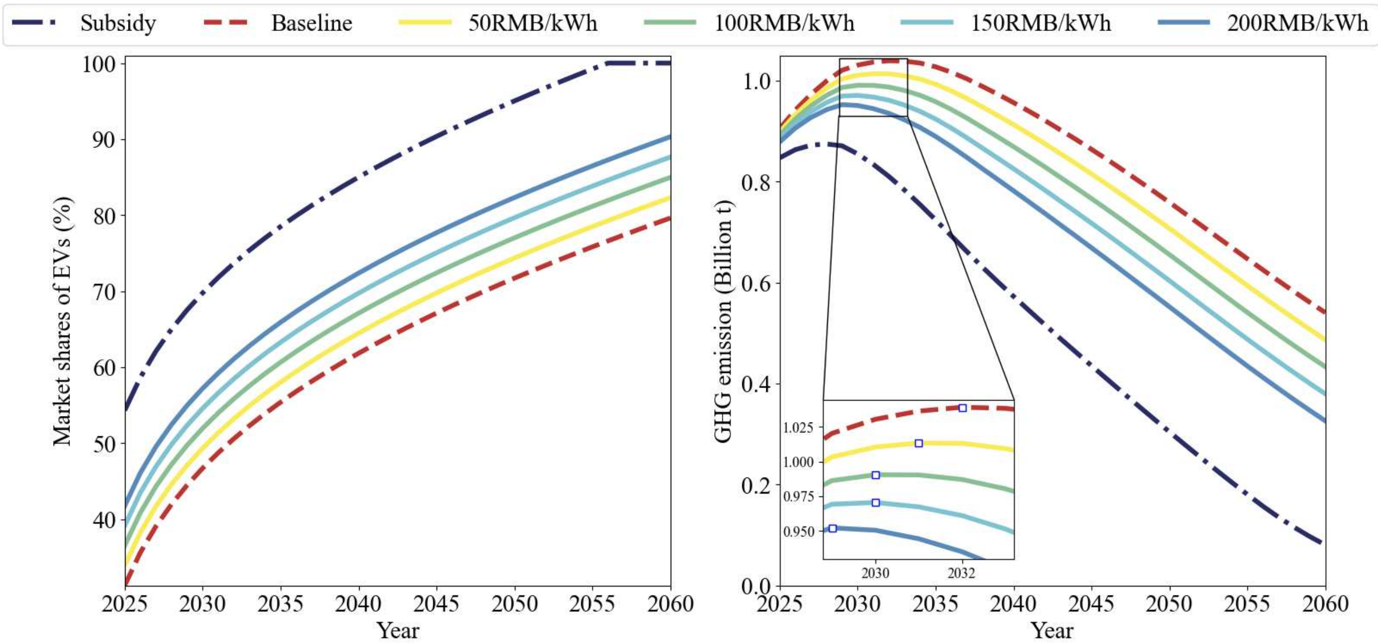

Fig. 16. Market shares of EVs (a) and GHG emission of private passenger vehicle sector (b) in different prices of battery recycling.

3.2.5 Economic benefit analysis

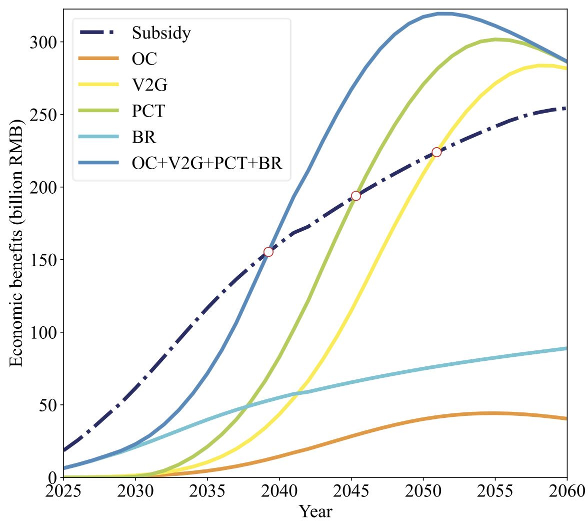

Fig. 16. Economic benefits of reducing social cost of GHG relative to the baseline in multiple scenarios.

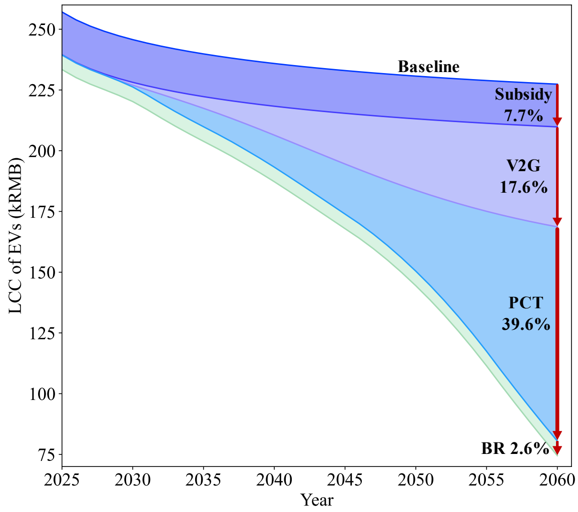

Fig. 17. The average LCC of EV users in multiple scenarios.

The implementation of purchase subsidy policy and usage-based incentives is projected to yield substantial economic benefits for both society and consumers. The policy parameters for this analysis are aligned with those delineated in Section 3.2.1. The social cost of Greenhouse Gas (GHG) emissions refers to the economic impact of damages incurred by each additional ton of GHG released[42]. According to Figure 16, the economic advantages of diminishing the social cost of GHG through Vehicle-to-Grid (V2G) and Personal Carbon Trading (PCT) for road transport are anticipated to surpass those of the purchase subsidy policy by 2051 and 2046, respectively. On the contrary, the battery recycling incentive is posited to yield more substantial economic benefits in the initial stages of implementation. The combination of multiple usage-based incentives is projected to culminate in a maximum economic gain of 319.37 billion RMB. After 2055, a marginal decline in the economic benefits of certain use-side incentive scenarios is observed, as comprehensive electrification within the private passenger vehicle sector would have been achieved, thereby diminishing the total GHG emission differential from the baseline scenario (see Figure 13(b)).

Furthermore, as illustrated in Figure 17, the contributions of V2G, PCT for road transport, battery recycling, and the purchase subsidy policy to the reduction of the average Life-Cycle Cost (LCC) for EV users in 2060 are estimated to be 17.6%, 39.6%, 2.6%, and 7.7%, respectively. These percentages are subject to change over time. This data suggests that PCT for road transport could offer the most significant economic benefits to EV users. In summary, in the long-term perspective, usage-based incentives, when applied with optimal intensity, are more effective in reducing GHG emissions compared to purchase-side incentives, and thereby, offer greater economic benefits to both society and consumers.

3.3 Sensitivity analysis

Although the inherent subjectivity entailed in the parameter configurations, the employment of sensitivity analysis serves as a crucial tool to investigate the variability of results under divergent configurations of key parameters [14]. Assuming that PCT for road transport will be implemented in 2030, this study delves into the impacts of various key factors - namely the license plate restrictions for ICEVs, the carbon pricing, and the GHG emission factor of electricity - on the GHG emissions within the private passenger vehicle sector. These factors are analyzed considering a fluctuation range of ±30%, with the findings graphically represented in Figure 18.

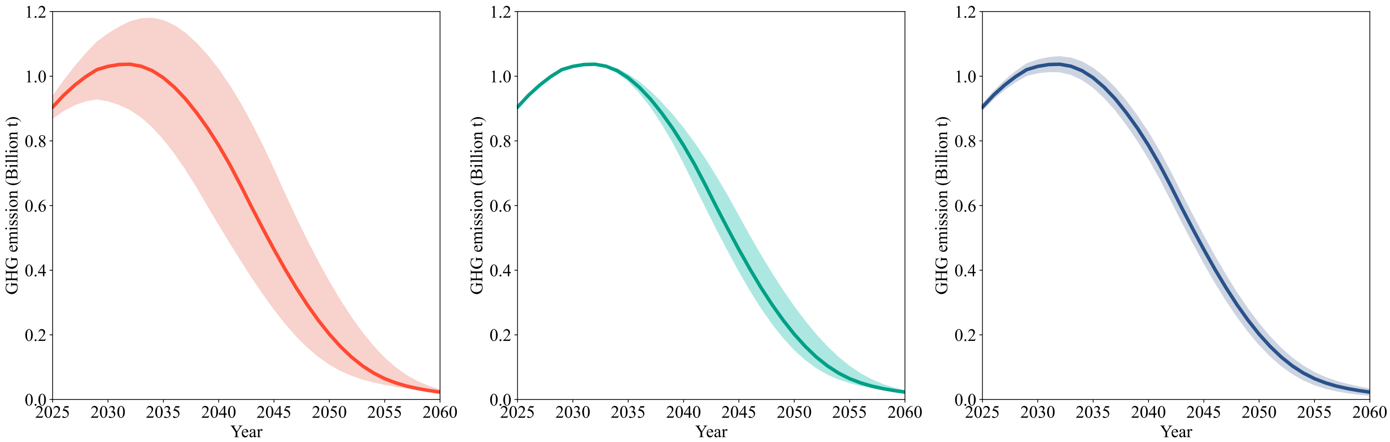

Fig. 18. Sensitivity analysis of the GHG emissions of private passenger vehicle sector to license plates restriction of ICEV (a), carbon price (b), and GHG emission factor of electricity (c).

The results shown in Figures 18(b) and 18(c) indicate that an elevated carbon price and a reduced GHG emission factor for electricity contribute to lowing the usage cost of EVs while simultaneously increasing those of ICEVs. This dynamic exerts an indirect influence on consumer purchasing decisions, albeit within a constrained scope. With the PCT for road transport is assumed to start in 2030, the influence of carbon pricing supersedes that of the GHG emission factor for electricity after 2038. On the other hand, an intensification of license plate restrictions for ICEV directly propels consumers towards EVs, significantly enhancing their market shares and effectively facilitating the reduction of GHG emissions. Consequently, the intensity of license plates restriction of ICEV holds the most substantial impact on GHG emissions within private passenger vehicle sector.

4. Conclusions and implications

In this study, a novel System Dynamics combined Agent-Based Modeling framework is developed, accounting for the diverse decision-making behaviors among distinct agents and forecasting the market shares of Electric Vehicles (EVs) and Greenhouse Gas emissions in the private passenger vehicle sector under various policy scenarios. The key conclusions and implications are as follows:

1. Vehicle-to-Grid (V2G) emerges as a more efficacious long-term policy for GHG emission reduction in the private passenger vehicle sector compared to EV purchase subsidies. V2G not only decreases the use-phase costs of EVs, thereby accelerating their market penetration, but also enhances grid load balancing through the integration of renewable energy sources, maximizing the energy efficiency and emission reduction potential of EVs. Consequently, more investments in charging infrastructure, especially in bidirectional charging stations, and incentivizing user participation in V2G programs are encouraging.

2. The implementation of Personal Carbon Trading (PCT) for road transport demonstrates a more pronounced impact on GHG reduction compared to V2G. PCT for road transport incentivizes EV usage, which indirectly influences consumers' preference for energy-efficient EVs. Furthermore, an optimal carbon pricing threshold can drive automakers to improve the fuel efficiency of ICEVs or transition to EV production, thereby stimulating R&D investments and fostering the growth of China's carbon trading market.

3. To achieve carbon neutrality in the private passenger vehicle sector by 2060, supplementary measures are required. As evidenced in Figure 11, the combined OC+V2G+PCT+BR scenario in 2060 nearly achieves a carbon-neutral state in the private passenger car sector, with EV ownership nearing 100% and GHG emissions at 0.022 billion tons. However, this goal is contingent on the GHG emission factor of electricity, necessitating initiatives such as grid decarbonization and carbon capture and storage to realize complete zero-carbon emissions.

4. From a broader perspective, usage-based incentives, particularly V2G and PCT for road transport, yield more

substantial emission reduction effects and economic benefits in the long term compared to purchase subsidy policies. These incentives also demonstrate enhanced sustainability.

5. Given the notable early-stage advantages of battery recycling, it can serve as a complementary measure to other use-side policies. Additionally, recycled batteries can be repurposed for energy storage systems, indirectly reducing GHG emissions associated with battery production in other sectors.

The analytical framework of this paper can also provide insights for the promotion of EVs and macroscopic GHG emission forecasts in other countries. Future research directions may include: (1) The adaptability of the model across different regions; (2) The progression of other types of alternative fuel vehicles, such as fuel cell electric vehicles; (3) The impact of various carbon quota allocation methods on consumer choices; (4) A long-term evaluation of emissions from the reuse of recycled batteries and other waste materials.

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